Commercialization of Distribution System Load Modeling Tool for Improved DER Interconnection Studies

Jiyu Wang,[1] Xiangqi Zhu,[1] Barry Mather,[1] and Ming Wu[2]

1 National Renewable Energy Laboratory
2 GitHub

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Contract No. DE-AC36-08GO28308

Technical Report
NREL/TP-5D00-89073
June 2024

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NOTICE

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1 Background

Residential and commercial buildings have huge potential to contribute value to improve grid resilience by participating grid services. To reveal the significant value, it is critical to estimate the grid service capability from these buildings. Unlike the large-scale distributed energy resources such as wind and solar farms, those buildings need to participate grid services in aggregation, not by individual. Therefore, it is important to appropriately group buildings for aggregation. The load profiles in the same group will have similar characteristics at the same time step, so grid operators can send the grid service signal to the customer group with a higher chance to respond at that time step. In this project, we develop a load profile clustering method to classify the building-level load profiles for grid service capability estimation.

2 Load Profile Clustering Method

2.1 Load Profile Clustering Algorithm

In this study, a two-step load profile clustering method is proposed to group the load profiles with similar characteristics and patterns. The load profiles will be clustered based on their energy consumption level in the first step, then the profile in each energy group will be further clustered based on the load shape. The flowchart of the proposed load profile clustering algorithm is shown in Fig. 1. First, the raw advanced metering infrastructure measurements from smart meters will be preprocessed to exclude the data with missing or bad measurements. This process will also extract the data from the desired period that we want to cluster. Then the extracted load profiles will be clustered to M groups based on the energy consumption level. Next, the profiles in each energy group will be further clustered to N_i clusters. These clusters will be the final clustering results, and the total number of clusters can be calculated by:

$$N_{tot} = \sum_{i=1}^{M} N_i \tag{1}$$

where N_{tot} is the total number of clusters, M is the total number of energy groups, and N_i is the total number of clusters in each energy group. The K-means clustering method is used for both steps, with the Euclidean distance selected as a reference for clustering, and the clustering results are used as the ground truth.

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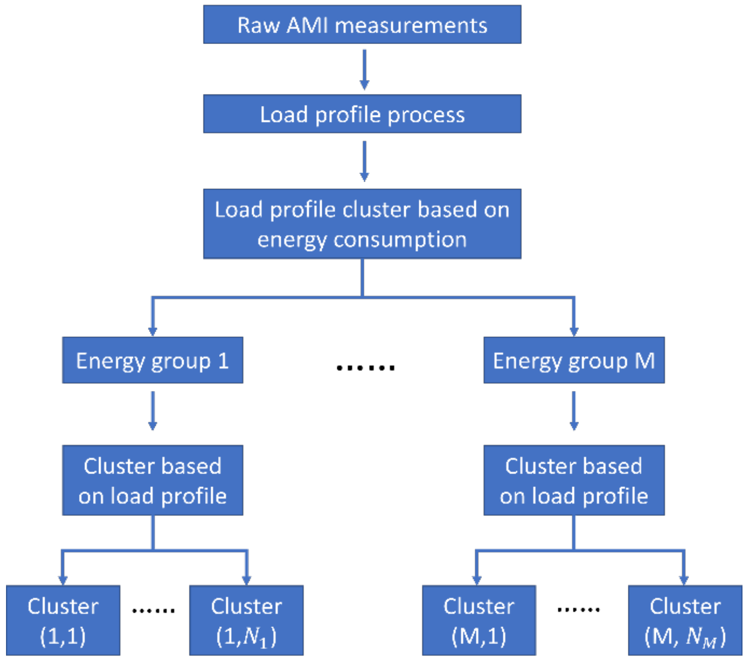

Figure 1. Flowchart of the proposed load profile clustering algorithm

After the initial K-means clustering, multilayer perceptron (MLP) method is used to classify the new incoming load profiles. MLP is a supervised learning algorithm that learns to classify by training on a data set. It is a feed-forward artificial neural network model that maps sets of input data to a set of appropriate outputs. An MLP consists of multiple layers, and each layer is fully connected to the following one. The nodes of the layers are neurons with nonlinear activation functions, except for the nodes of the input layer—these nodes rely on this underlying neural network to perform the task of classification. In this study, the MLP is trained with the clustering results from the K-means.

2.2 Load Profile Clustering Algorithm Results

In this study, the parameters for the K-means are first tested for the energy consumption-level clustering. A total of 2,000 daily load profiles are clustered by the K-means clustering algorithm, and different numbers of predefined clusters are tested. Because the large number of profiles and their daily energy consumption ranges from 0 to 5,000 kWh, the number of clusters are tested from 8 to 15. For each case, the K-means clustering algorithm is conducted, and the silhouette score is calculated. In addition to the silhouette score, the size of each cluster is considered as an evaluation criterion for the results. We define the clusters with less than 5 profiles as a "small cluster" and clusters with more than 50 profiles as a "large cluster." Ideally, the results should have more large clusters and fewer small clusters so that each cluster can represent a typical case. The test results in Fig. 2 show that the silhouette score is stable when the number of clusters are between 8 and 12. After considering the number of small clusters and large clusters, we selected the case when there are 9 clusters to be the best result. In the clustering process, this procedure should be repeated for all energy groups to select the best number of clusters for all cases.

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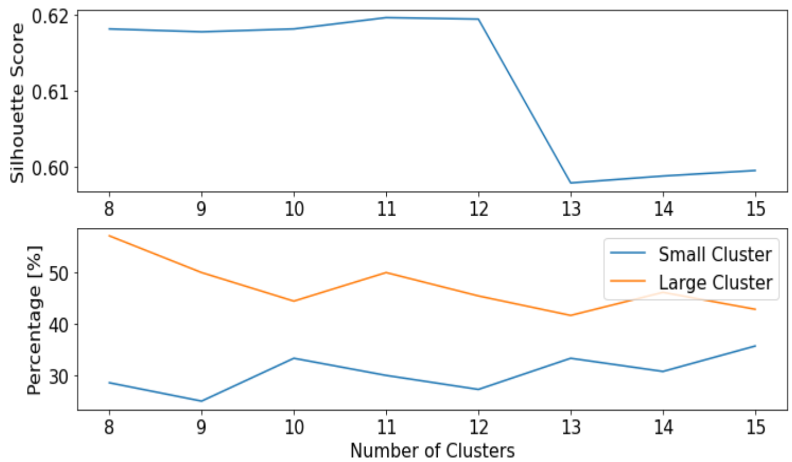

Figure 2. Parameter test for the K-means clustering on energy consumption level

To calculate the success rate of the proposed algorithm, first, we used K-means to cluster 2,000 load profiles into 9 energy groups. Based on the number of load profiles in each energy group and the K-means parameter selection process, we determined the number of subgroups in each energy group, and we used K-means to further cluster them. The total number of clusters is 37, and the clustering results are used to train the MLP model. While training the MLP classifier, the number of hidden layers and the number of cells in each layer need to be predefined. We tested the performance with different parameters, and one example result is presented in Table 1. the highest silhouette score occurs when there are 5 hidden layers and 4 cells in each layer. Similar to the process in the K-means parameter selection, this procedure should be repeated for all clusters to select the best parameters for all cases.

Table 1. Parameter Test on MLP Model for Load Shape Classification

Silhouette score					
		Number of hidden layers			
		3	5	7	9
Number of cells in each layer	4	0.36	0.59	0.34	0.58
	5	0.16	0.25	0.25	0.26
	6	0.01	0.25	0.22	0.23
	7	0.23	0.24	0.15	0.19
	8	0.15	0.21	0.17	0.24
	9	0. 11	0.25	0.15	0.28

Then we used the trained MLP model to classify the 2,000 load profiles and compare the results with the original ground truth from the K-means. The example center profiles for the low, medium, and high energy groups are shown in Fig. 3, Fig. 4, and Fig. 5, respectively. The center profiles

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between ground truth and cluster results are very similar, which proves the effectiveness of the clustering method.

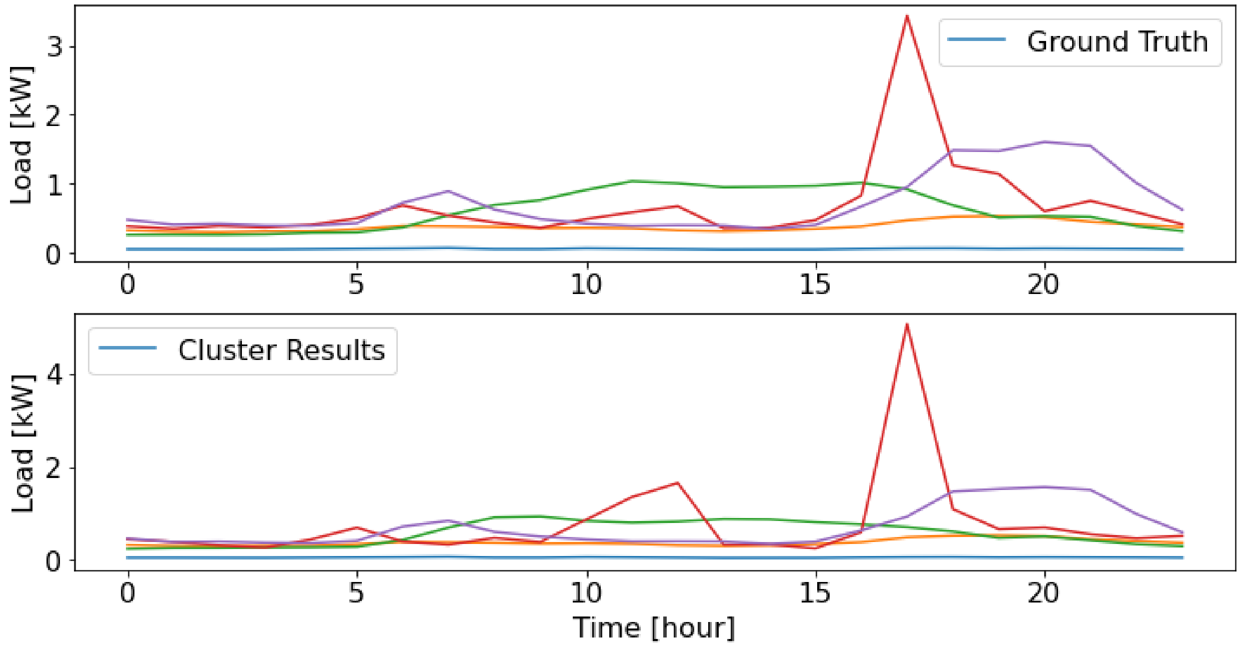

Figure 3. Center profiles for the low energy groups

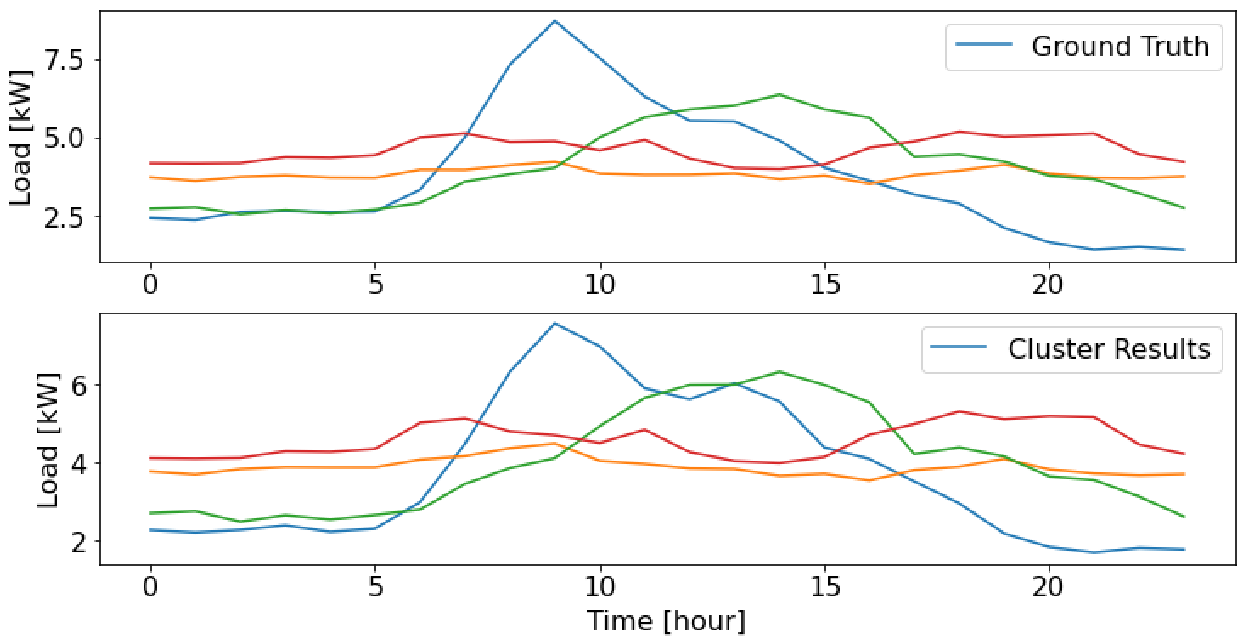

Figure 4. Center profiles for the medium energy groups

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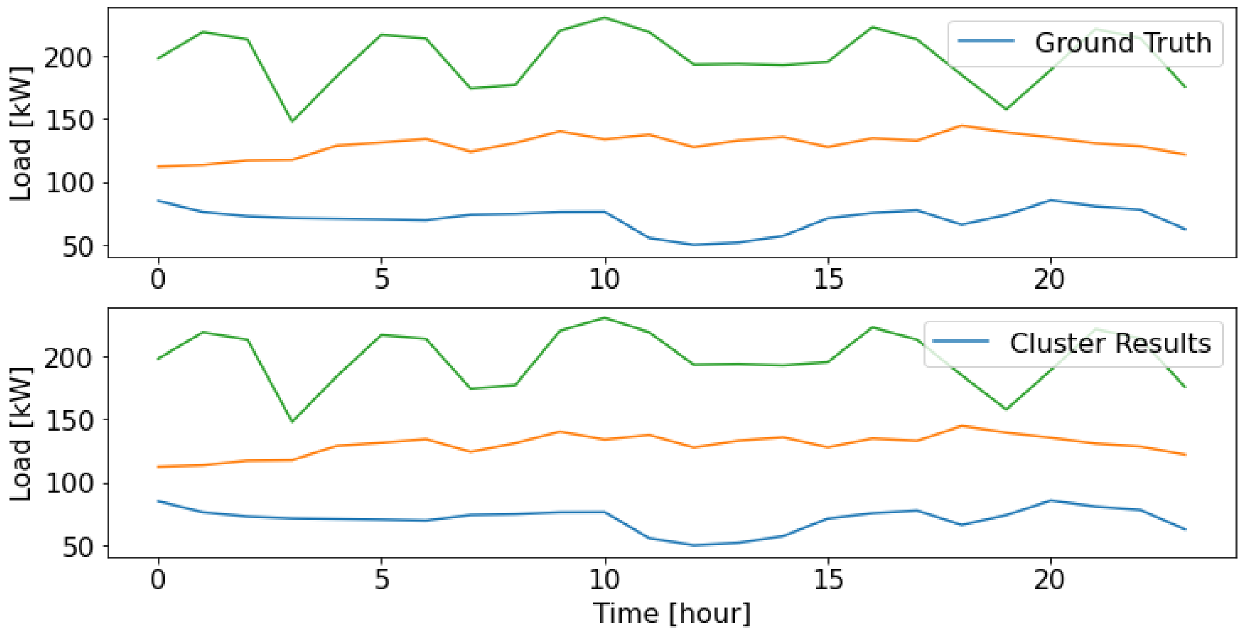

Figure 5. Center profiles for the high energy groups

The success rate for each energy cluster is shown in Fig. 6. The success rate is calculated by:

$$SR = \frac{n_r}{n_t} \tag{2}$$

where n_r represents the number of load profiles recognized in the group, and n_t represents the total number of profiles that need to be recognized in this group. There are 9 energy clusters and 37 total clusters. First, the success rate for each energy cluster is calculated. The results show that the success rate for all the energy clusters is greater than 90%, and most of them are greater than 95%. The result shows that 1,902 out of 2,000 load profiles have the same clustering results compared to the ground truth. Overall, the success rate is 95.1%, which means that this satisfies the 90% target in our milestone.

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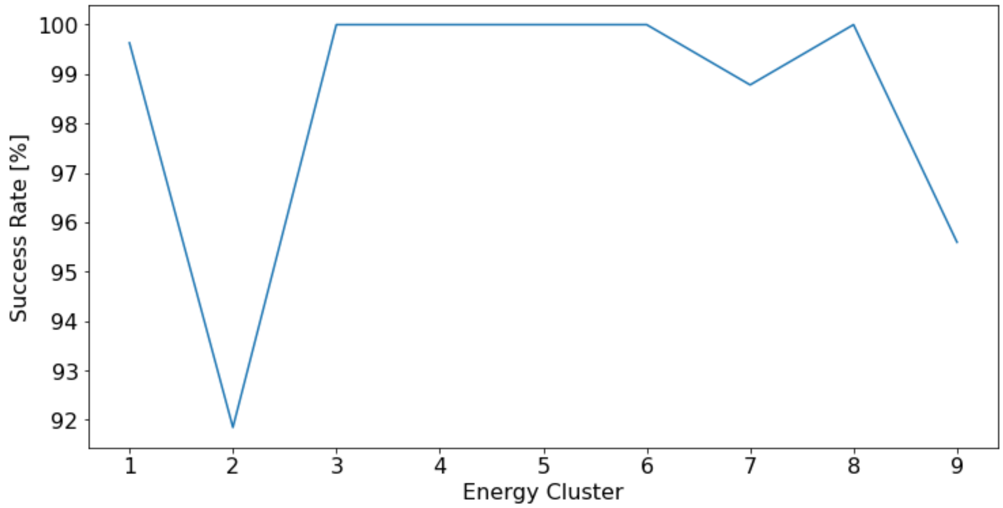

Figure 6. Success rate of each energy cluster

The factors that create difficult cases were studied. Three factors were tested to investigate how they impact the success rate: the number of profiles, the number of clusters, and the average distance of the load profiles. We tested to select different numbers of profiles from 30 to 2,000 (30, 50, 100, 150, 200, 300, 500, 1,000, 1,500, 2,000). The different load profile distance was selected for different test cases. For example, the average distance is 2.57 when we tested the first case with 500 profiles. Then the load profiles for the second case with 500 profiles has an average distance of 7.1. For each group, we tested the results with the number of clusters from 3 to 15 (3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15). In total, 780 different cases were created, and the success rates were calculated for each case.

After the success rate for all these cases were calculated, linear regression was used to calculate the coefficients, as in (1):

$$SR = x_1 * n_t + x_2 * N_c + x_3 * D + x_0 \quad (3)$$

where SR represents the success rate, n_t represents the total number of profiles, N_c represents the total number of clusters, D represents the average distance of the load profiles, and x_0, x_1, x_2, x_3 are the coefficients to be calculated. The linear regression results can help to understand the relationship between each factor and the final success rate. The factor with a higher coefficient means it has more impact on the success rate, which help us determine the best clustering settings.

The regression results are shown in Fig. 7. The dots are the actual success rates for three different cases, and the lines show the estimated success rates from the regression results. We define that a success rate less than 92% is a difficult case. The results in Fig. 7 (a) and (b) show that the success rates is lower when there are more profiles, more numbers of clusters, and fewer average profile distances.

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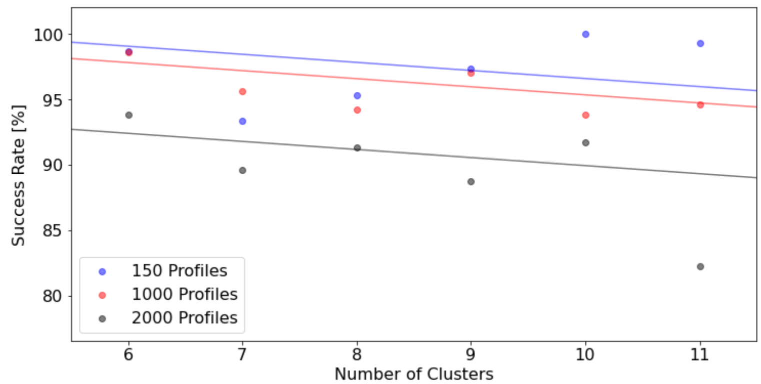
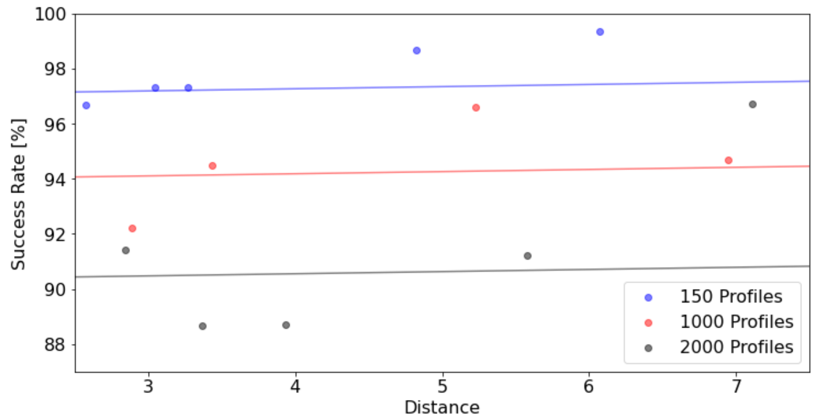


(a) Regression results with the number of profiles and the number of clusters



(b) Regression results with the number of profiles and distances

Figure 7. Regression results based on the success rate (x_1=-0.0000363, x_2=-0.00618, x_3=-0.000779, x_0=1.0306)

To quantify the relationship between different cases and different factors, a score for the evaluation is defined in (2):

$$Score = \frac{1000*D}{n_t*N_c} \tag{4}$$

The results are shown in Fig. 8. The first subplots in Fig. 8 (a) and Fig. 8 (b) show the success rates, and the second subplots show the evaluation scores. In general, the difficult case occurs more often when the score is less than 0.5. The solution for the difficult case is to select an appropriate number of clusters. Because the number of profiles and average profile distance is usually fixed for one clustering problem, one way to solve the difficult case is to select an appropriate number of clusters. The results shown are for our difficult case, which we defined as having a success rate less than 92%, but this number might be different for other cases; however, we can still use this method to quantify that criterion.

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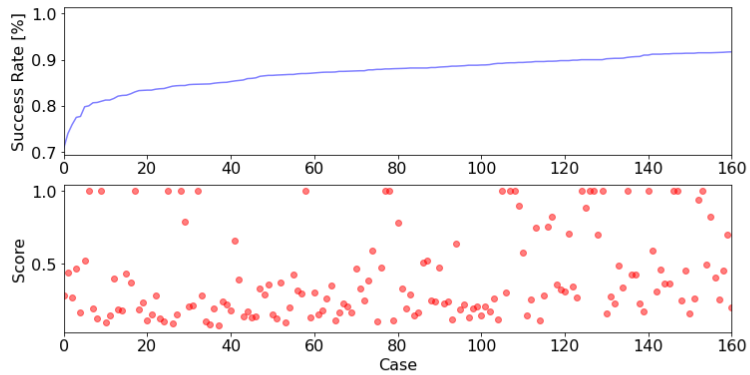
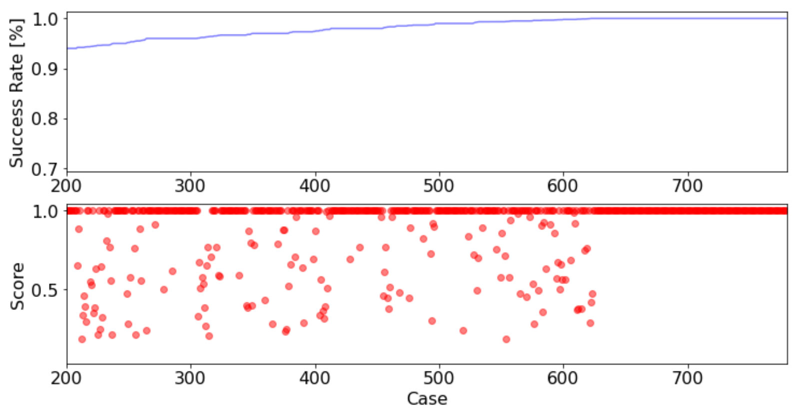


(a) Success rate and evaluation score Part 1



(b) Success rate and evaluation score Part 2

Figure 8. Success rate and evaluation scores

2.3 Representative Load Pattern Generation

With the load profile clustering algorithm, we aim to develop 50 representative load patterns for the default load pattern library of the NREL developed advanced load scenario and analysis tool (ALSAT). The original development of this tool concept was to enable the development of high-temporal resolution, realistic time-series load profile data for quasi-static time-series (QSTS) analysis of distribution systems. ALSAT can close the gap of distribution load modeling needs in the market. It can take limited smart meter/customer transformer data and model the loads in the whole distribution circuit in realistic detail, enabling more accurate DER integrated simulation analysis and better preparing utilities for critical future operational scenarios. The crest factor is used to evaluate the differences between different load patterns, which can be calculated by:

$$CF = \frac{x_{peak}}{x_{rms}} x_{peak} \tag{5}$$

where:

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \cdots x_n^2)} \tag{6}$$

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Here, the $|x_{peak}|$ represents the peak value of a load profile, and $x_1 \cdots x_n$ represents the data points in the load profile. The crest factor for all representative load profiles will be compared by (5), and it is expected that they will be 10% different from each other.

$$0.1 \leq \frac{|CF_n - CF_m|}{CF_n} \tag{7}$$

To select 50 representative load profiles, we used the proposed clustering algorithm to cluster the 2,000 load profiles, and we selected 50 profiles. We selected the center profile of each group as one potential representative load profile, and we calculated the crest score. All 50 profiles have at least 10% difference with other profiles. The shapes of the 50 representative profiles are shown in Fig. 9. Most profiles have very different shapes, and for some similar shapes in this figure, the peak loads and energy consumption levels are different. These representative profiles will be added to the demonstration diversity library of ALSAT.

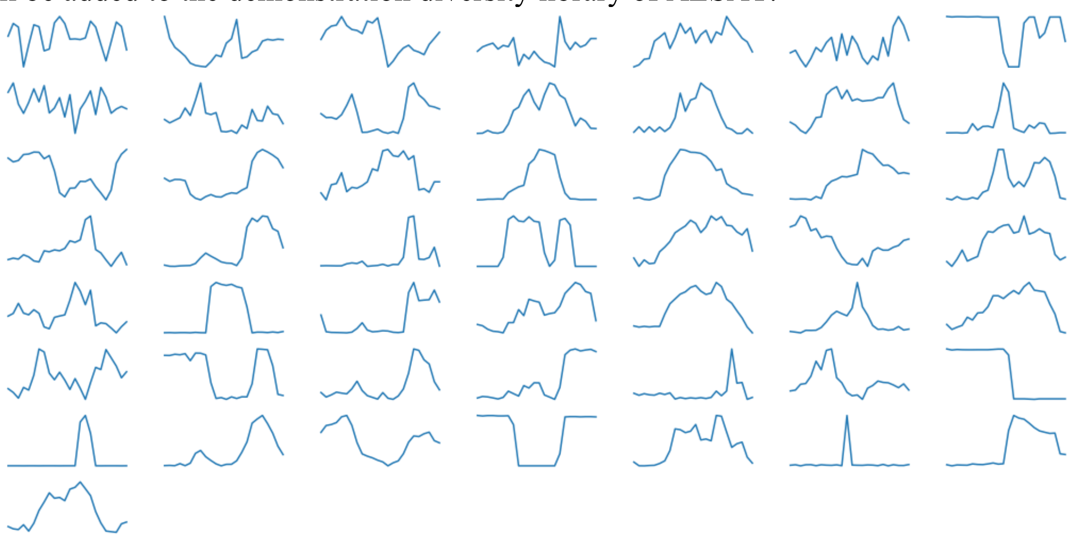

Figure 9. Shapes of 50 representative profiles

3 Graphic User Interface of ALSAT

3.1 Graphic User Interface Design

The graphical user interface (GUI) of ALSAT is developed and the main design of this GUI is shown in Fig. 10. There are three modules in this tool: (1) Instruction and Status, (2) Library and Profile Generation, and (3) Results Analysis. The detailed functions of each module are described in detail in the following subsections.

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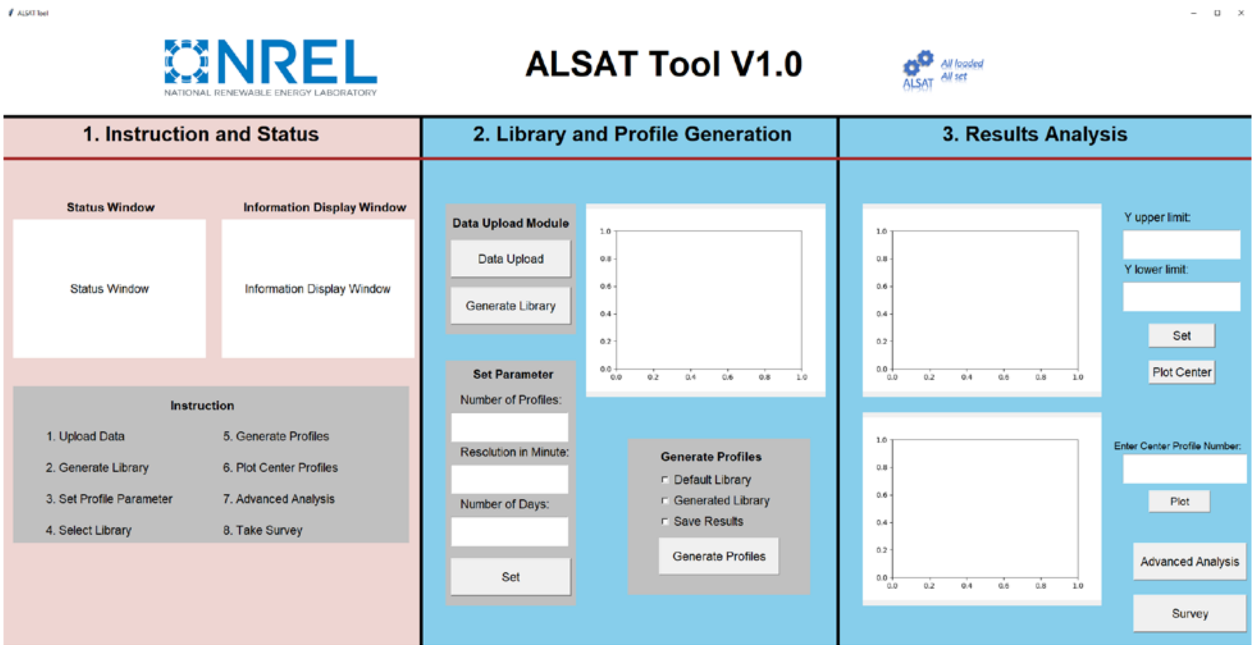

Figure 10. Main design of ALSAT GUI

3.1.1 Instruction and Status

In the Instruction and Status module, users can read the status and information of this tool. For example, after the data are uploaded, the "Status Window" will show "Upload Finished," and the number of profiles, data resolution, and data duration will be shown in the "Information Display Window." The instruction part presents the procedure of using this tool. Once one step is complete, the text of this step changes to green to notify the user, as presented in Fig. 11.

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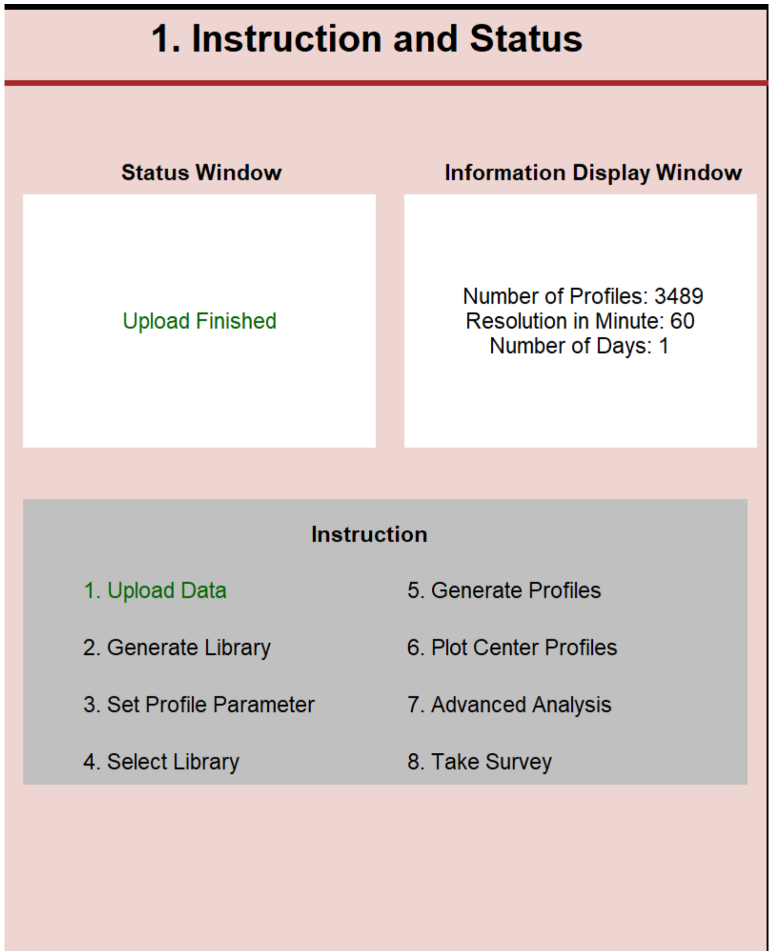

Figure 11. Instruction and Status module

3.1.2 Library and Profile Generation

In the Library and Profile Generation module, users can first upload their load profile database by clicking on "Upload Data." The "Status Window" will show "Upload Finished" when it finishes. The tool will summarize the number of load profiles in the load profile database in the "Information Display Window." After the data are uploaded, users can click on "Generate Library" to generate the load profile library. The tool will use the load profile database as the input and run the two-step load profile clustering algorithm. The silhouette score will be calculated for the clustering results. The tool will give users a suggestion on whether the default library or the generated library should be used based on the silhouette score. After the library is generated, the next step is to generate the synthetic load profiles. First, users need to set the parameters for the synthetic profiles, including the number of profiles, the data resolution in minutes, and the data duration in days. Then users can select whether to use the default library or the library generated with the load profile database. By clicking on "Generate Profiles," the synthetic profiles will be generated and plotted. If the users want the result to be saved, the authors also need to check the "Save Results" option.

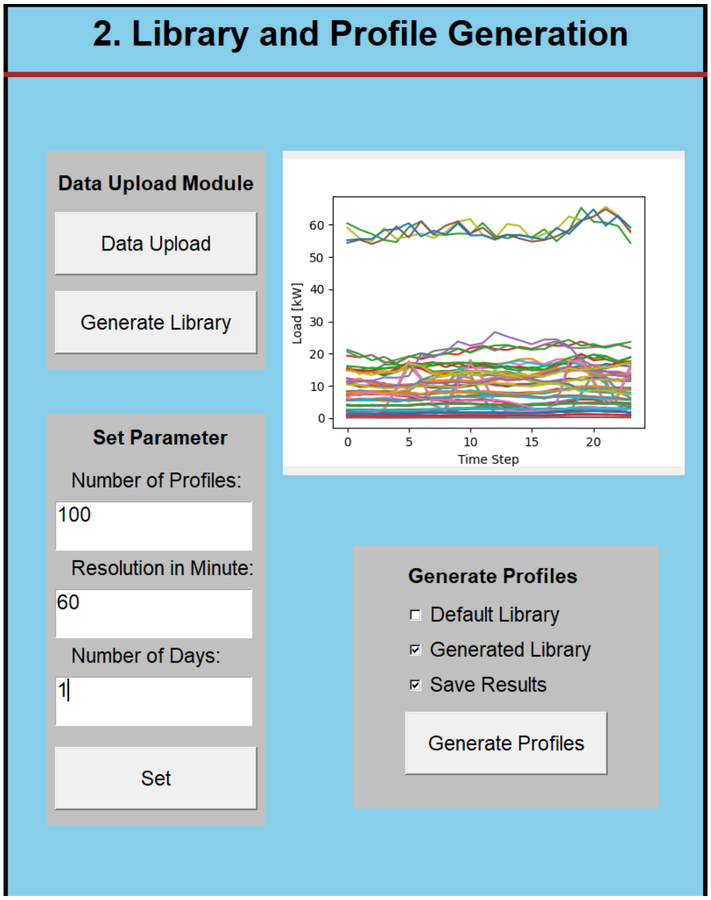

Figure 12. Library and Profile Generation module

3.1.3 Results Analysis

In the Results Analysis module, users can obtain the analysis of their results. Authors can plot all the center profiles or plot each individual center profile. By clicking on "Advanced Analysis," users can view the peak load, the average load, and the peak load ratio of the center profile in each cluster. Note that all the results shown in these plots are intermittent for testing while developing this GUI. The actual load profile database and library will be implemented once the development of this tool is finalized. Finally, users can click on "Take Survey" and submit their user experience feedback to the developers. The survey includes the following:

1) I understand what ALSAT does.
2) I know how to use ALSAT.
3) The prompts displayed for the inputs are clear.
4) Learning to operate this tool is easy.
5) You would like to recommend a colleague to use this tool.
6) What do you find best about this tool?

After users respond to the six questions, there is one more black text box for users to submit other feedback for this tool.

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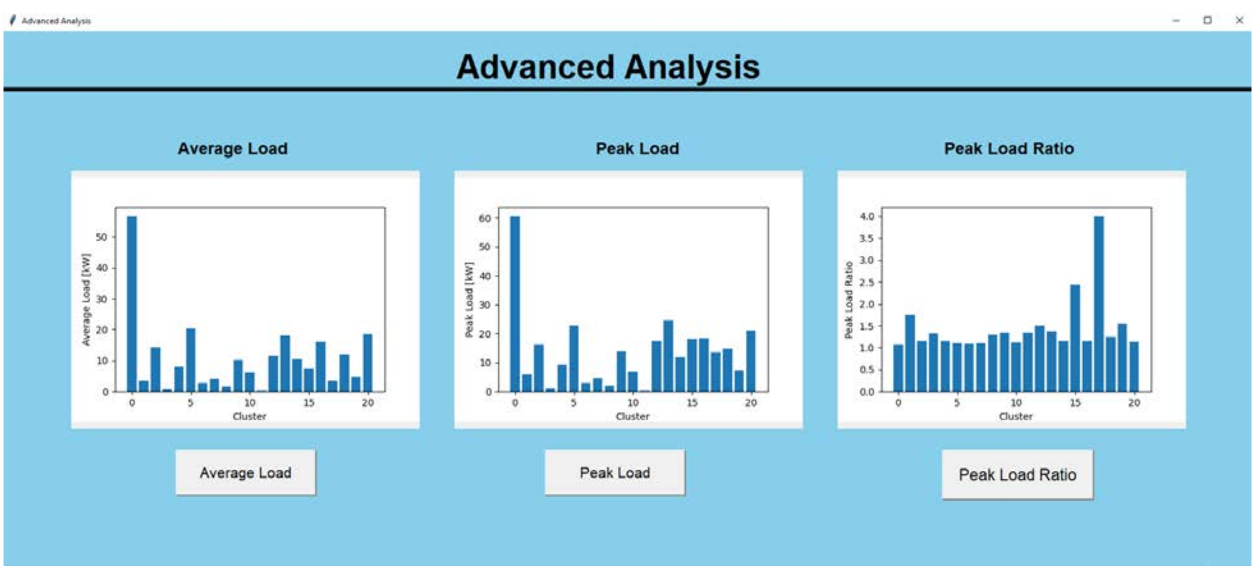
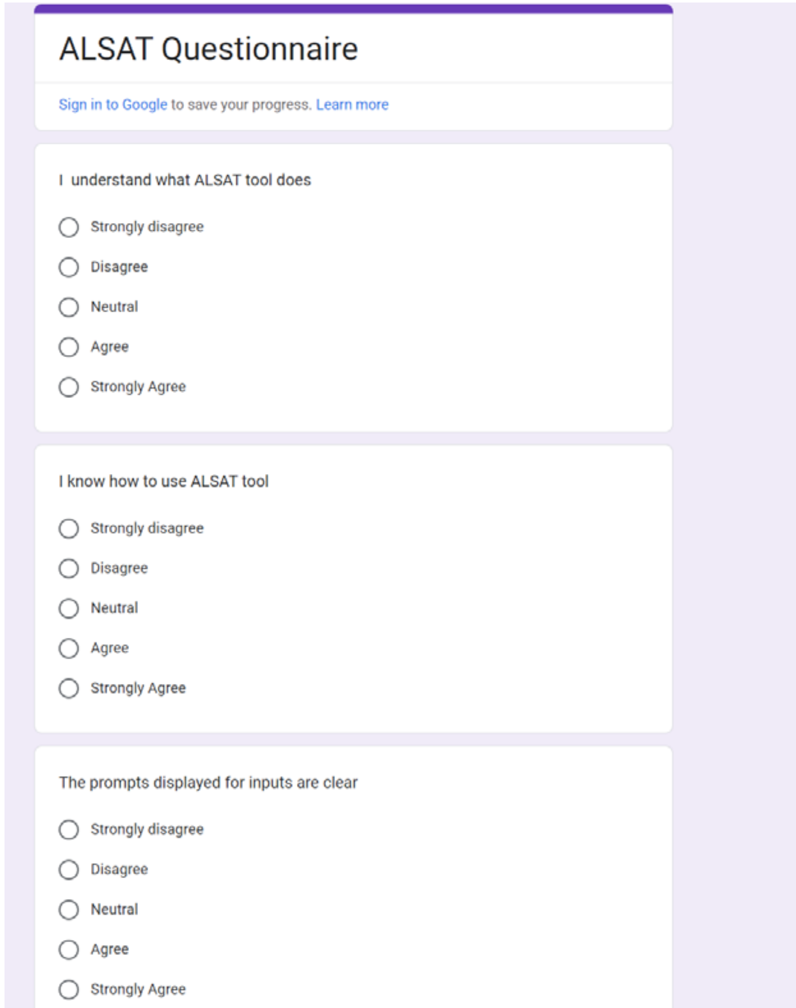
(a) Results Analysis



(b) Advanced Analysis



(c) ALSAT Questionnaire

Figure 13. Results analysis function

3.2 User Survey

ALSAT has been distributed to people with different background including people working in technology company and students, and 8 responses have been received. The feedback has been collected and is shown in Fig. 14. The responses are from technology companies and students. Overall, the score is 96.5 out of 100. The provided features are the best aspect of this tool for most people. Because of the time constraint, at present, we have received 8 responses, and they are all from technology companies or students.

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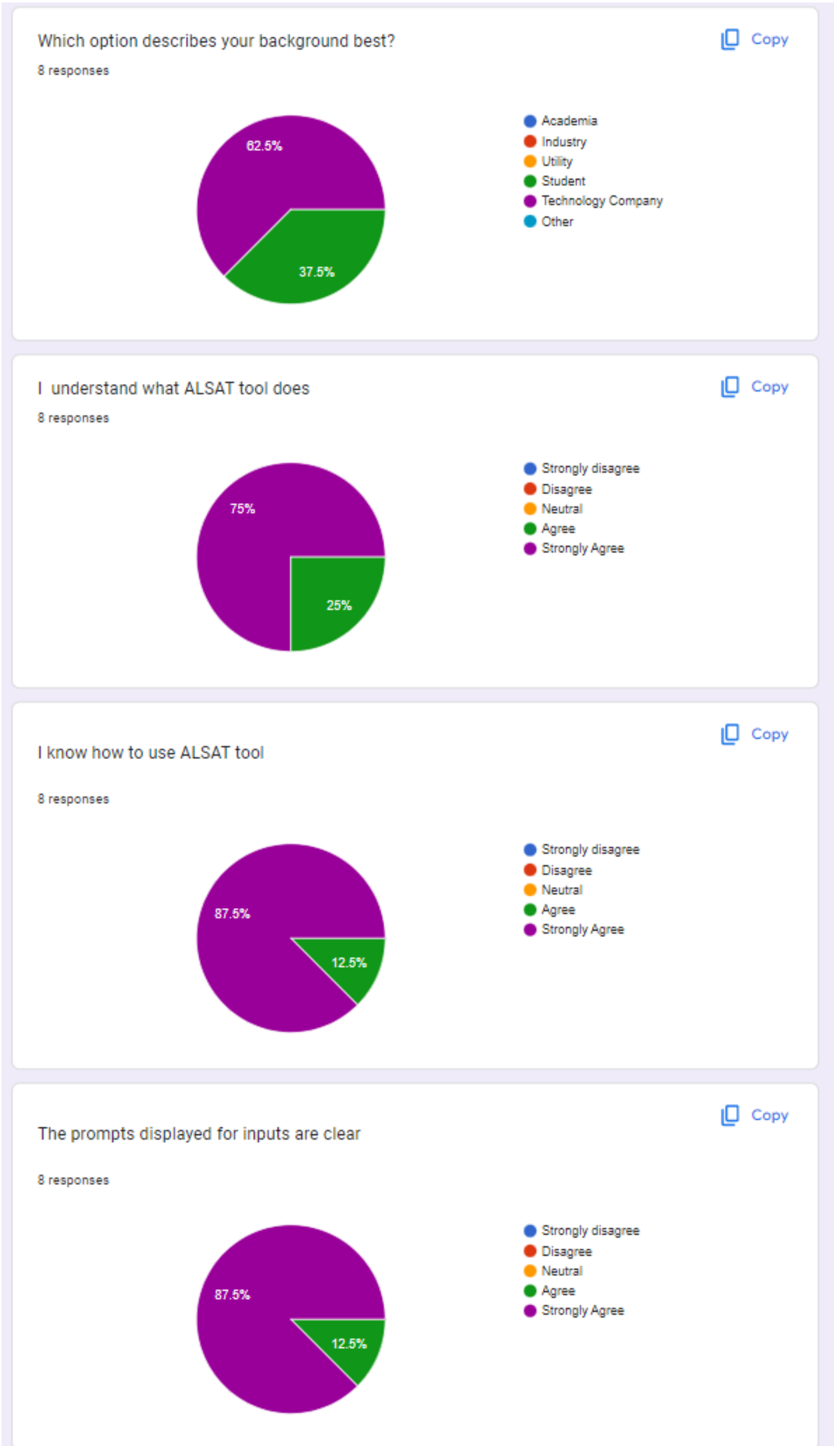
Which option describes your background best?
Copy
8 responses
62.5%
37.5%
Academia
Industry
Utility
Student
Technology Company
Other
I understand what ALSAT tool does
Copy
8 responses
75%
25%
Strongly disagree
Disagree
Neutral
Agree
Strongly Agree
I know how to use ALSAT tool
Copy
8 responses
87.5%
12.5%
Strongly disagree
Disagree
Neutral
Agree
Strongly Agree
The prompts displayed for inputs are clear
Copy
8 responses
87.5%
12.5%
Strongly disagree
Disagree
Neutral
Agree
Strongly Agree

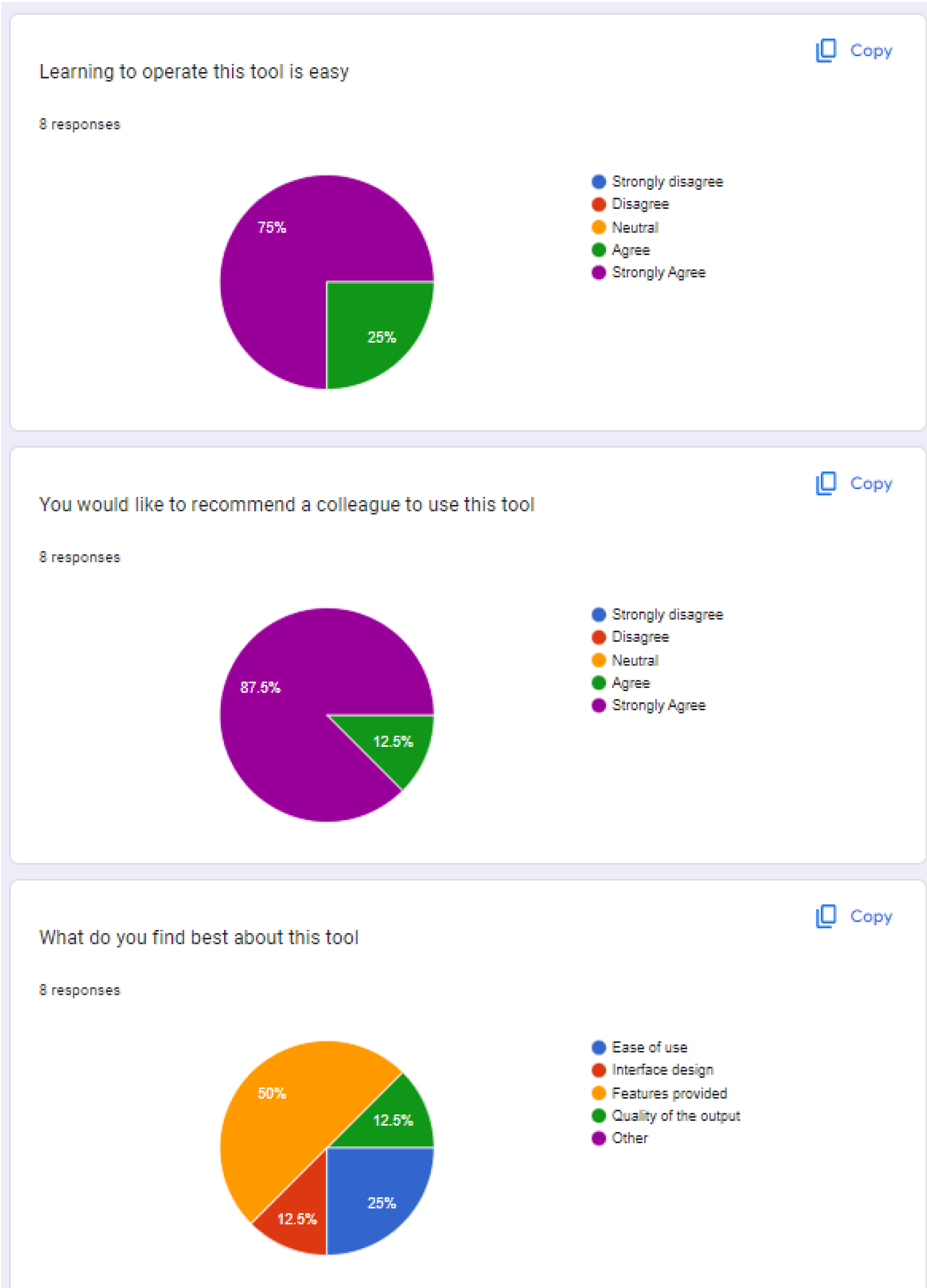

Figure 14. ALSAT GUI survey results

4 Conclusion

The commercialization target in this project is the ALSAT tool which we developed in our previous SETO project. The main function of ALSAT is to take existing measurements from part of the distribution system/territory and output load profiles for all the individual customer nodes in the system/territory with representative and realistic diversity and variability. With ALSAT, the users can easily get *All* the nodes in their distribution system *loaded* with diversified load profiles, then all the remaining system analysis and management control systems are *All set* for accurate time-series analysis needed for modern interconnection and operational studies.

In this project, we've focused on the two initial steps of ALSAT commercialization, which are:

1) Technology upgrade. One key upgrade we've done is expanding our diversity and variability library, providing enough representative profiles for tool demonstration and user test runs. Another important upgrade is advancing our profile generator, providing users a computation efficient approach for profile clustering and representative profile generation.

2) User interface design. User interface is a critical step for tool commercialization. With the help from Microsoft expert Dr. Ming Wu, we've learned the interface design procedure and test metrics deployed by professional businesses. After several iterative discussions with Dr. Wu, we've designed our user-friendly interface with minimum operation efforts and concise instructions. With the test results, we are proud to see an 96.5% satisfactory rate.

5 Industry Partner Engagement

By closely engaging with the tool's commercialization process, our industry partner Dr. Ming Wu from Microsoft have contributed valuable insights, resources, and expertise to ensure its successful launch and adoption in the market:

1. **Co-development**: We work closely with Dr. Wu to co-develop and refine the tool, receiving valuable industry-specific insights, data, and expertise to ensure the tool meets the needs of real-world applications.

2. **Validation and Testing**: We collaborate on field testing and validation of the tool within real-world power distribution systems, gathering feedback and validating the tool's effectiveness.

3. **Market Research and Feedback**: We actively engage Dr. Wu in market research activities to identify target markets, understand customer needs, and gather feedback on the tool's features and usability.

4. **Continuous Improvement**: We've been maintaining an ongoing collaboration with Dr. Wu for continuous improvement of the tool, incorporating her feedback and evolving market demands to ensure long-term success and customer satisfaction.

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6 Publications

[1] J. Wang, X. Zhu, and B. Mather. " A Two-Step Time-Series Data Clustering Method for Building-Level Load Profile.", accepted by PESGM 2023

[2] J. Wang, X. Zhu, and B. Mather. " Demographic Information Incorporated Household Energy Consumption.", accepted by PESGM 2023

[3] J. Wang, X. Zhu, B. Mather, and M.Wu. " Demographical Information Incorporated Geographical Grid Service Capability Estimation Paradigm.", in preparation

[4] D. Rice, Y. Wang, J. Wang, X. Zhu, and B. Mather. " Bayesian Matrix Power Usage Behavior Clustering.", in preparation

7 Reference

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