Investigation of Alternative Power Distribution and Optimal Configuration through the Implementation of Clustering Algorithms-Based Microgrids for a Case Study

D. M. Li Kwok Cheong, T. Fernando, H. Iu, M. Reynolds, and J. Fletcher

Abstract—**This paper presents a novel approach to optimizing rural electrical power transmission network. The primary objective of this project is to determine an optimal (more economical) network configuration for a case study where large portions of network assets are approaching the end of their life cycle. Therefore, this is the most opportune time to redesign, and implement economically beneficial distribution alternatives such as microgrids and standalone power systems and, to evaluate the economic benefits of a combination of distribution alternatives. The latter alongside multiple microgrids have often been overlooked by past studies. Using Minimum Spanning Trees (MSTs) and clustering algorithms, the ideal location of microgridsand combination of distribution alternatives can be investigated. The results obtained from this study suggest that implementing microgrids and standalone power systems, drastically reduce the total cost of the network when compared to anoverhead transmission MST network. Furthermore, a combination of an overhead network with microgrids and standalone power systems resulted in the most economical network configurations.**

Index Terms—**Distribution network, K-means, microgrids, standalone power systems.**

I. Introduction

Optimizing network performance and reliability at the lowest possible investment cost have become challenges that current electrical utility companies attempt to tackle [1]. In areas where users are spatially isolated, there is an increased investment required to connect them to a network and this results in decreased returns for the network operators [2]. Optimization of the network by implementing newer, more reliable and cost effective power generation and/or distribution technologies, is a potential solution for the aforementioned problem.

As renewable technologies are sustainable, supply power locally, and decrease operation and transmission lines costs [3], electrical utility companies have strived to integrate these with power distribution alternatives. One such alternative is microgrids, which both improve the reliability of the network and are economically beneficial [4], [5]. As past research has been focused on the implementation and control of microgrids, less emphasis has been placed on the development of an optimal distribution network formation algorithm involving microgrids. Additionally, multiple smaller microgrids in a single region or a combination of power distribution alternatives have not been investigated.

A method to achieve multiple smaller microgrids is through clustering algorithms, which amasses points into clusters based on their spatial arrangement. Clustering algorithms were utilized in wireless sensor networks [6] and optimal location planning of social services facilities such as schools and hospitals [7], [8]. Essentially, this can also be applied to microgrids, as the location of the distributed energy generators (DEG) and resources (DER) is critical to impact the maximum number of users.

This paper focuses on a case study of an electrical network located in Kondinin Shire, Western Australia. As part of the Western Australian network underwent "significant expansion 40 years ago, and up to 80% of the installed distribution overhead network will be subjected to renewal in the next 20 years" [2], this presents the opportunity to potentially upgrade and/or redesign the distribution network.

The main objective of this study is to determine an economically beneficial network configuration through the utilization of clustering algorithms-based microgrids. This entails a comparison of the power distribution alternatives such as centralized distribution networks (SPL), standalone power systems (SPS), microgrids (MG) and an amalgamation of all three. A Minimum Spanning Tree will be employed in SPL and MG clusters to simulate the possible transmission lines.

II. Clustering Algorithms

Clustering algorithms can be categorized as hierarchical, partitioning, grid based, density based or model based algorithms [7]. Clustering involves the distribution of a set of objects into different groups. During this case study, the following categories of algorithms were considered: hierarchical and partitioning.

A. Hierarchical Clustering

Hierarchical clustering algorithms can be formulated bottom-up (Agglomerative) and top-down (Divisive), and can proceed one of three ways; single-linkage cluster (shortest distance between clusters), complete-linkage cluster (greatest) and average-linkage cluster (average) [9]. Agglomerative

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hierarchical clustering (AHC) assigns a cluster to each object and proceeds to combine the closest pairs of clusters. The algorithm recalculates the distance between the clusters (new and old clusters), continuing until all the objects are in one cluster [10], [11]. Divisive hierarchical clustering (DHC) proceeds in reverse by splitting the furthest clusters, continuing until all objects are not in clusters.

Traditionally, DHC is unused due to the expensive computational power required [12], issues with the relative order of the separation of the subgraphs and lack of indication of "when to stop splitting" [13]. Therefore, AHC was employed during this study.

B. Partitioning Clustering

K-means (KM) is an unsupervised learning algorithm [14] and a basic partition clustering technique from which, K-medoids (KMD) and Fuzzy K-means have been derived [15]. K-means is an algorithm which initially selects K number of centroids (center/mean location of clusters) from the dataset and assigns the remaining objects to the closest center. The new average/mean location of the cluster is calculated and the algorithm is repeated until no further change is observed in the centroid placement [16].

K-medoids is a variant of K-means, which only considers objects from the dataset as centroids in lieu of the mean location in a cluster. Fuzzy K-means employs a probability model which assigns each point with a different "degree of belonging" to a cluster, such that all objects affect the calculation of new centroids [17]. During this study, only the KM and KMD algorithms were considered.

III. Microgrids

Dating back to 1882, microgrids are defined as smaller distribution networks consisting of DER and DEG for power storage and generation [5], [18]. Microgrids can be categorized as islanded and grid-connected [19]. Compared to islanded microgrids, grid-connected microgrids remainconstantly connected to the main distribution network and employ the islanded microgrids format (disconnected from grid network)as emergency power sources [20]. Often, grid-connected microgrids are used in closed communities such as university campuses where electrical power is concrete to the business's operations [21] whilst islanded microgrids are employed in remote and isolated locations [19]. As the primary objective of this study was to reduce the distribution cost in rural distribution networks, therefore the islanded microgrid format was employed. Additionally, a reference microgrid architecture/topology was defined for cost estimations and comparison of the different distribution alternatives.

IV. Optimal Network Approach(es)

Prior to commencing any analysis, the case study area had to be partitioned into four sections to preventoverlaps of the microgrid clusters formed with the pre-existing three phase backbone (TPL) of the network. To adequately compare the power distribution alternatives available, networks using each of the alternatives (SPL, SPS and MG) were generated for each partitioned section. In the MG network analysis, each of clustering algorithms was tested separately. For the partitioning clustering algorithms (KM and KMD), the value of K ranged from 1 to N-1[1] with N being the number of users in a partitioned section. The AHC algorithm restricted the number of possible clusters to a subset of {1, N-1}. If a cluster contained one user, it was redefined as a SPS instead.

SPL and SPS networks involved connecting all users to a centralized distribution network or separate standalone power systems respectively. The SPS cost was associated with the distribution transformers required if the user was connected to a SPL network. A maximum distribution transformer rating of 50 kVA was implemented due to the equipment prices available. Therefore, if the SPS rating was greater than 50 kVA, the user was connected using only SPL or MG. For both MG and SPL, the transmission cost to connect all users was determined through a Minimum Spanning Tree (MST).

To obtain the optimal network architecture (i.e. network with the lowest total cost), two approaches were designed. Noting that the cost of a viable MG cluster (transmission and generation equipment) is less than the cost of implementing the cluster users as SPL or SPS and that all viable clusters with only one user were defined as SPS, the following methods were employed.

A. Approach #1

Using a distance threshold, approach #1 restricted the possible SPL users to those located adjacent to the TPL (within a distance margin/threshold). This resulted in users located distant to the TPL with a SPS rating greater than 50 kVA, being identified as MG nodes only. The remaining users located far from the TPL were assigned to a MG cluster or as SPS. Fig. 1 represents a flowchart of approach #1.

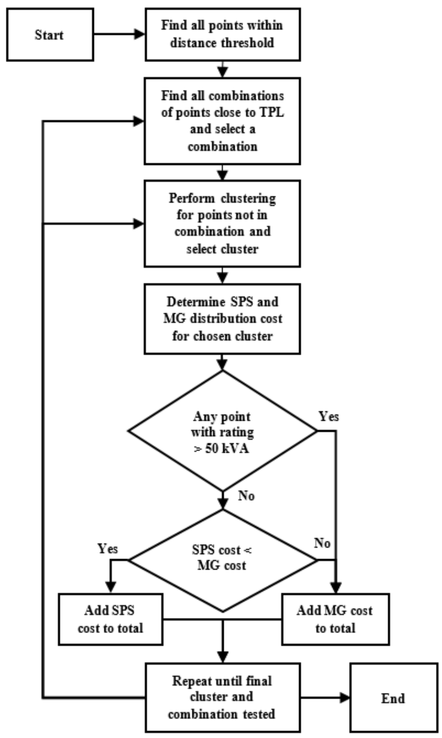

Fig. 1. Flowchart of approach #1.

[1] N-1 is the maximum number of clusters as with N-1, this would still involve the clustering of two points whilst the rest are standalone.

B. Approach #2

In approach #2, all viable MG clusters were first identified followed by an assignment of the remaining points as SPL or SPS. No distance threshold was implemented. Fig. 2 outlines the approach #2 procedure.

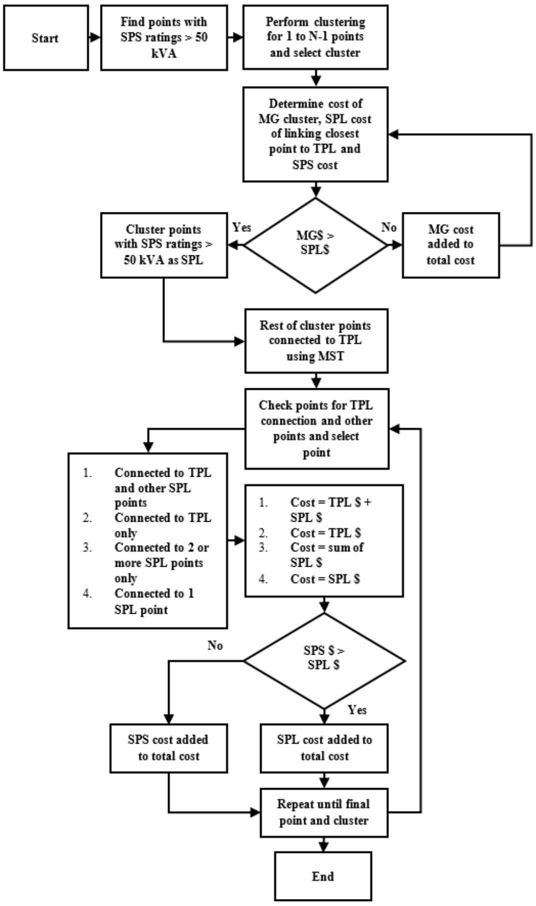

Fig. 2. Flowchart of approach #2.

V. Results and Analysis

Fig. 3 represents the case study area and spatial arrangement of the TPL and users. The size of the area is 70 km by 45 km and contains 208 users. Using the TPL (bold line) as the primary boundary, four sections (as indicated by the red lines) of varying sizes were obtained.

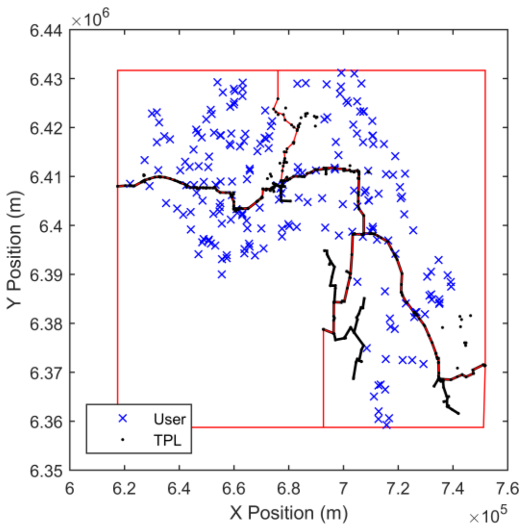

Fig. 3. Case study partitioning and spatial arrangement of users.

A. Optimal Network

Fig. 4-Fig. 7 represent the North West, North East, South West and South East sections of the optimal network respectively. The North-West network (Fig. 4) was obtained by using approach #2 and AHC. In this section, a large proportion of MG clusters contained two users, five SPL viable nodes were present and the remaining users were suitable as SPS. Implementing a combination of SPL, SPS and MG resulted in the most economical solution. The network costs of the SPL (MST), SPS only and MG (includes SPS) network were 337.5%, 211.3% and180.9% of the optimal network cost.

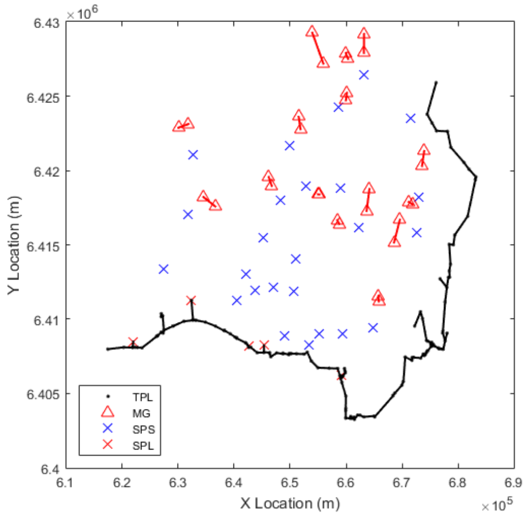

Fig. 4. North West section of the optimal network.

As approach #1 and KMD were employed to determine the optimal network layout in the North-East partition (Fig. 5), the viable SPL could only be observed adjacent to the TPL. MG clusters of various sizes could be found close (further than the distance threshold) to the TPL. The SPL (MST) network costed 331% of the optimal network, 232.7% for the SPS only and 128.7% for the MG network. The largest percentage difference between an SPS only and optimal network occurred in this section**.**

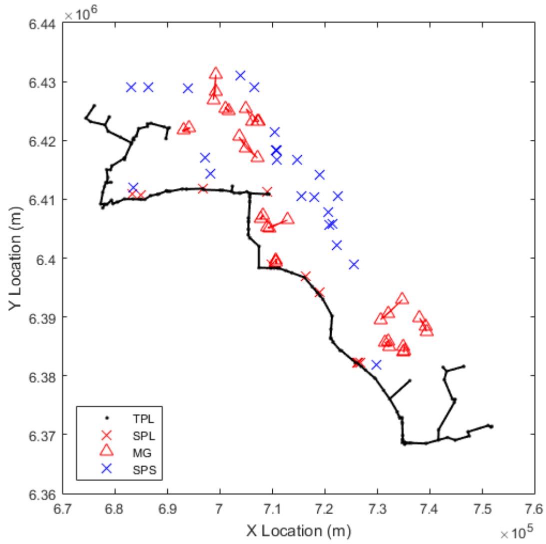

Fig. 5. North East section of the optimal network.

The optimal network of the South West partition (Fig. 6) primarily contained MG clusters with two users, and 11 SPL viable locations. The remaining points unsuitable for MG or SPL were identified as SPS nodes. This was obtained through approach #2 and KM. Relative to the cost of the optimal network, which implements MG, SPS and SPL, the SPL (MST), SPS only and MG networks costed respectively 371.4%, 217.3% and 186.2% (largest for all sections)of the optimal network.

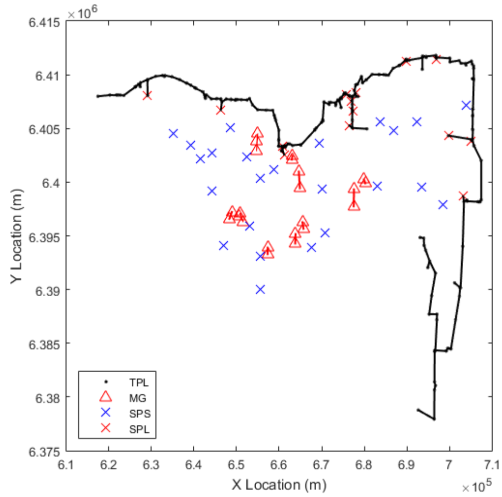

Fig. 6. South West section of the optimal network.

The South-East partition (Fig. 7) was the smallest partition and had the lowest user count. Employing each approach and clustering algorithm combination, the cost and topology of the optimal networks were nearly identical. Though a network solution was recurrent, this did result in the lowest possible cost. Using approach #2 and KMD to find the optimal solution, the SPL (MST) network is 487.2% (largest out of all partitions), SPS only is 161.5% and 138.5%, for the MG network, of the optimal solution cost.

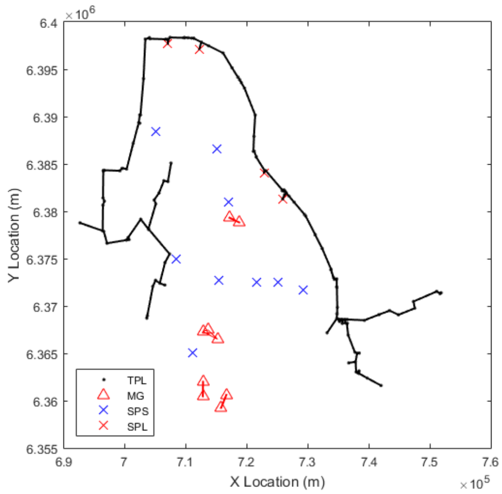

Fig. 7. South East section of the optimal network.

B. Clustering Algorithms

Out of the four partitioned sections, networks obtained through KMD costed, on average, less than the other clustering algorithms. However, the results suggest that an ideal/ all-purpose clustering algorithm, which could consistentlyobtain more cost-effective clusters, was not amongst AHC, KM and KMD (refer to Table I and Table II). Therefore, further research is required to determine an ideal clustering algorithm.

TABLE I: COMPARISON OF OPTIMAL NETWORK PERCENTAGE COST DIFFERENCES BASED ON CLUSTERING ALGORITHM USED FOR APPROACH #1

Clustering algorithm	AHC	KM	KMD
	North West section		
AHC	-	-3.28%	-4.13%
KM	3.17%	-	-0.83%
KMD	*3.97%*	*0.82%*	-
	North East section		
AHC	-	9.17%	12.48%
KM	-10.10%	-	3.64%
KMD	*-14.27%*	*-3.78%*	-
	South West section		
AHC	-	-33.50%	-39.29%
KM	25.09%	-	-4.34%
KMD	*28.21%*	*4.16%*	-
	South East section		
AHC	-	4.97%	4.97%
KM	-5.23%	-	0.00%
KMD	*-5.23%*	*0.00%*	-

TABLE II: COMPARISON OF OPTIMAL NETWORK PERCENTAGE COST DIFFERENCES BASED ON CLUSTERING ALGORITHM USED FOR APPROACH #2

Clustering algorithm	AHC	KM	KMD
	North West section		
AHC	-	-1.35%	-3.38%
KM	1.34%	-	-2.00%
KMD	*3.27%*	*1.96%*	-
	North East section		
AHC	-	-4.35%	1.19%
KM	4.17%	-	5.30%
KMD	*-1.20%*	*-5.60%*	-
	South West section		
AHC	-	2.76%	1.99%
KM	-1.82%	-	-0.50%
KMD	*-2.03%*	*0.78%*	-
	South East section		
AHC	-	4.97%	6.02%
KM	-5.23%	-	1.11%
KMD	*-6.41%*	*-1.12%*	-

C. Power Transmission Alternatives

A comparison of the lowest network cost for different distribution alternatives (Table III), suggests a positive relationship between the implementation of SPS/MG and SPL. The cost of the SPS and MG network were consistently lower than the cost of the SPL (MST) network. Additionally, implementing MG further optimized the SPS network by clustering certain users. Hence, these results suggest that the implementation of power distribution alternatives other than SPL, reduces the investment required.

Furthermore, implementing a combination of all distribution alternatives further optimized the network, which was suggested by the percentage cost difference between the MG solutions (which employ clusters and SPS) and the optimal network. Nonetheless as the equipment prices and transmission costs were estimates, further research is required to provide more accurate analysis of the distribution alternatives.

TABLE III: COMPARISON OF DISTRIBUTION ALTERNATIVES RELATIVE TO OPTIMAL NETWORK

Optimal section network	Distribution alternatives			
	Optimal	SPL	SPS	MG
North West	100%	337.5%	169.9%	116.4%
North East	100%	331.0%	232.7%	128.7%
South West	100%	371.4%	217.3%	186.2%
South East	100%	487.2%	161.5%	138.5%

VI. CONCLUSION AND FUTURE WORK

The introduction of microgrids has been seen to improve the cost and reliability of power distribution network and has altered the stigma associated with power distributions [3]. Steering away from the traditional overhead network and implementing microgrids and/or standalone power systems, might potentially provide new alleyways for development. Particularly, the results from this study has shown that an implementation of different distribution alternatives might be more economically beneficial for the network operators. The limitations of this study were the case study size and consequently the partitioned sections, the cost estimates (e.g. cost for SPS ratings greater than 50 kVA) and the adaptability of the algorithm to larger regions.

Though the results do suggest that the implementation of standalone power systems and microgrids may improve the cost efficiency, further work and research are required to improve the cost estimates (equipment and transmission cost), adaptability of the algorithm, and clustering algorithms employed.

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REFERENCES

[1] M. Li, C. Yanyan, Y. Yingjie, Z. Chunlei, Q. Zhengmei, L. Wei, C. Xuefeng and Y. Haiming, "Distribution network optimize planning based on operation efficiency and benefits," in *Proc. 2016 China International Conference on Electricity Distribution (CICED)*, Xi'an, 2016.

[2] J. Fletcher, T. Fernando, H. Iu and M. Reynolds, "A case study on optimizing an electrical distribution network using a genetic algorithm," in *Proc. 2015 IEEE 24th International Symposium on Industrial Electronics (ISIE)*, Buzios, 2015.

[3] M. Ding, Y. Zhang, and M. Mao, "Key technologies for microgrids-a review," in *Proc. 2009 International Conference on Sustainable Power Generation and Supply*, 2009.

[4] Y. Zhou and C. N.-M. Ho, "A review on Microgrid architectures and control methods," in *Proc. 2016 IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia)*, Hefei, 2016.

[5] S. N. Bhaskara and B. H. Chowdhury, "Microgrids — A review of modeling, control, protection, simulation and future potential," in *Proc. 2012 IEEE Power and Energy Society General Meeting*, 2012.

[6] F. Belabed and R. Bouallegue, "An optimized weight-based clustering algorithm in wireless sensor networks," in *Proc. 2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, 2016.

[7] H. Salman, L. Ibrahim, and Z. Fayed, "Enhancing Clustering technique to plan social infrastructure services," in *Proc. 2013 4th International Conference on Intelligent Systems, Modelling and Simulation*, Bangkok, 2013.

[8] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor network," *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660 - 670, October 2002.

[9] S. Rana and R. Garg, "Application of hierarchical clustering algorithm to evaluate students performance of an institute," in *Proc. 2016 Second International Conference on Computational Intelligence & Communication Technology*, Ghaziabad, 2016.

[10] T. K. Jain, D. S. Saini, and S. V. Bhooshan, "Performance analysis of hierarchical agglomerative clustering in a wireless sensor network using quantitative data," in *Proc. 2014 International Conference on Information Systems and Computer Networks (ISCON)*, Mathura, 2014.

[11] M. Scalzo and S. Velipasalar, "Agglomerative clustering for feature point grouping," in *Proc. 2014 IEEE International Conference on Image Processing (ICIP)*, Paris, 2014.

[12] R. Xu and D. Wunsch, "Survey of clustering algorithms," *IEEE* Transactions *on Neural Networks*, vol. 16, no. 3, pp. 645-678, 2005.

[13] S. E. Schaeffer, "Graph clustering," *Computer Science Review*, vol. 1, no. 1, pp. 27-64, 2007.

[14] G. Singh, J. Kaur, and Y. Mulge, "Performance evaluation of enhanced hierarchical and partitioning based clustering algorithm (EPBCA) in data mining," in *Proc. 2015 International Conference on Applied and Theoretical Computing and Communication Technology (ICATCCT)*, Davangere, 2015.

[15] S. Baadel, F. Thabtah, and J. Lu, "Overlapping clustering: A review," in *Proc. 2016 SAI Computing Conference (SAI)*, London, 2016.

[16] P. Chauhan and M. Shukla, "A review on outlier detection techniques on data stream by using different approaches of K-Means algorithm," in *Proc. 2015 International Conference on Advances in Computer Engineering and Applications (ICACEA)*, Ghaziabad, 2015.

[17] E. Hot and V. Popović-Bugarin, "Soil data clustering by using K-means and fuzzy K-means algorithm," in *Proc. 2015 23rd Telecommunications Forum Telfor (TELFOR)*, Belgrade, 2015.

[18] S. Parhizi, H. Lotfi, A. Khodaei, and S. Bahramirad, "State of the art in research on microgrids: A review," *IEEE Access*, vol. 3, pp. 890-925, 2015.

[19] J. Clavier, M. Ross, and G. Joos, "Dispatch techniques for Canadian remote communities with renewable sources," in *Proc. 2013 IEEE Electrical Power & Energy Conference (EPEC)*, Halifax, 2013.

[20] C. Marnay, S. Chatzivasileiadis, C. Abbey, R. Iravani, G. Joos, P. Lombardi, P. Mancarella, and J. V. Appen, "Microgrid evolution roadmap," in *Proc. 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, Vienna, 2015.

[21] R. M. González, T. A. J. V. Goch, M. F. Aslam, A. Blanch, and P. F. Ribeiro, "Microgrid design considerations for a smart-energy university campus," in *Proc. 2014 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, 2014.

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