Algorithms to Manage Load Shedding Events in Developing Countries

Extended Abstract

Olabambo I. Oluwasuji
Electronics and Computer Science
University of Southampton, Southampton UK
oio1a14@soton.ac.uk

Obaid Malik
Electronics and Computer Science
University of Southampton, Southampton UK
O.Malik@soton.ac.uk

Jie Zhang
Electronics and Computer Science
University of Southampton, Southampton UK
Jie.Zhang@soton.ac.uk

Sarvapali D. Ramchurn
Electronics and Computer Science
University of Southampton, Southampton UK
sdr1@soton.ac.uk

ABSTRACT

Due to the limited generation capacity of power stations, many developing countries frequently resort to disconnecting large parts of the power grid from supply, a process termed load shedding. This leaves homes without electricity, causing them discomfort and inconvenience. Because fairness is not a priority when shedding load, some homes bear the brunt of these effects. In this paper, we present our ongoing research into considering fairness when shedding load at the household level.

KEYWORDS

Load shedding; Heuristics; Fairness; Developing countries

ACM Reference Format:

Olabambo I. Oluwasuji, Obaid Malik, Jie Zhang, and Sarvapali D. Ramchurn. 2018. Algorithms to Manage Load Shedding Events in Developing Countries. In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018*, IFAAMAS, 3 pages.

1 INTRODUCTION

Load shedding is very common in developing countries, because generation capacity is often insufficient for meeting demand, and the grid infrastructure is poorly maintained or obsolete. In Nigeria for instance, the total installed capacity of generating plants is under $8000MW$, which is grossly inadequate for serving a population of over 170 million people [10]. This makes load shedding a common occurrence in the country [4] and a prevalent problem that will be relevant for the near future. Load shedding entails systematically and deliberately cutting off the supply to parts of the network, so that the strain on the system is reduced and total grid collapse is prevented. Although load shedding ensures the stability of the network, no due consideration is given to what parts of the system are disconnected, in terms of when or how often they are disconnected. This results in some homes being left with irregular or no supply for days or weeks while others remain online. Additionally, for electricity providers, current practices of disconnecting parts of the grid may result in revenue loss, as more load than is required may be shed.

In light of the above, we present a novel approach to load shedding, where load is shed at the household level. Our approach models homes as agents, each with its own preferences for consuming energy. Specifically, our model attempts to manage the inconvenience of shedding events by applying different methods for fairly choosing which households to disconnect. These methods consider varying, and sometimes conflicting fairness criteria, including the number of times each agent is shed, the individual discomfort inflicted on agents when they are shed, the number of agents shed and the comfort costs incurred by the system. Using data from Pecan Street's Dataport[1], we evaluate our load shedding algorithms and show how they perform in optimizing utilitarian and egalitarian social welfare objectives, as well as minimizing envies.

2 MANAGING LOAD AT THE HOUSEHOLD LEVEL

Our approach to shedding load is based on previous research, where smart retrofitted household electric meters were designed for use in developing countries [2, 5]. The retrofits employ GSM modules as a medium of connection between individual meter and operator, thus enabling individual meters for remote disconnection and re-connection. Presented below are four heuristic algorithms that consider varying levels of fairness when shedding load at the household level.

2.1 Heuristic Household Load Shedding Algorithms

Suppose for each hour, there is a population of n agents (each with a demand), the aggregated hourly demand of all agents and the hourly supply capacity available for the entire population of agents. Then, if the hour's supply is less than demand, the deficit is the difference. Every hour there is a deficit, our heuristics disconnect a set of agents from supply using these procedures:

(1) The Grouper Algorithm (TGA) creates different groups of agents, such that the aggregate demand of each group is enough to

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

[1] Dataport is the largest provider of accessible disaggregated household energy consumption data [9].

offset the deficit. It creates these groups by randomly distributing agents into different sets, until the aggregate demand of the remaining agents is less than the deficit. After all groups are formed, TGA sums up the aggregated number of times the agents in each group have been disconnected from supply. Thereafter, TGA selects the group with the minimum aggregated disconnection.

(2) The Consumption-Sorter Algorithm (TCSA1) creates a sorted order for selecting agents from a population, based on hourly demand. From the population, TCSA1 selects agents one after another in the sorted order, until the sum of selected agents is enough to offset the deficit. Selected agents are removed from the population and added to a set. Since only the agents left in the population are available for selection, some agents are omitted in subsequent shedding operations. If the population set becomes empty, TCSA1 returns all agents into it, but ensures no agent is selected twice within the same shedding operation.
(3) The Random-Selector Algorithm (TRSA), unlike TCSA1, is agnostic to agents' demands. Thus, its major difference from TCSA1 is that it randomly selects agents from the population.
(4) The Cost-Sorter Algorithm (TCSA2), unlike TCSA1, creates sorted orders based on the agents' comfort costs (discussed in Section 3). Otherwise, it employs the same procedures as TCSA1.

For each of these algorithms, the set of selected agents is disconnected from supply.

3 PERFORMANCE EVALUATION

Given that there are currently no datasets available for hourly energy consumption at household levels for a large number of households in any developing country, we focus on developing a realistic simulation of energy consumption that can be attributed to households in *developing countries*. In particular, we focus on developing a dataset for households in Nigeria[2], where the residential sector accounts for 51.3% of consumption [7]. We do this by taking individual appliance level data from Dataport, then using only appliances found in a common Nigerian household [1, 3, 8, 11] to construct household level hourly consumption, while also taking into consideration the temperature similarity between Nigeria and Austin, Texas, the actual location from which the data was gathered[3]. From this, we produce the data for 382 households. The simulated data is used for implementing and evaluating the performance of our algorithms.

We formulate the comfort costs of agents from their weekly consumption patterns. First, we formulate an agent's consumption profile by computing the agent's average hourly consumption for a week (i.e. 168 hours) using prior four weeks' data. Then, we normalize the consumption profile to come up with the comfort costs. We posit that the comfort cost of an agent at hour (t) is the discomfort caused the agent, if it is disconnected at t.

For assessing the performance of our heuristics, we employ some predominant objectives in economic model design, namely the utilitarian, egalitarian and envy-freeness objectives [6, 12], and adapt these to our problem domain.

Table 1: Comparing economic fairness objectives, based on comfort costs

Heuristic	Utilitarian	Egalitarian	Envy-freeness
Grouper	50363.06	376.13	318.66
Consumption-Sorter	**50291.58**	**179.04**	**129.91**
Random-Selector	54665.61	197.27	141.44
Cost-Sorter	54386.10	213.95	152.57

In terms of comfort costs, an agent's negative utility is $u_{\delta}^{-} = \sum_{s=1}^{k} \delta_i(s)$, for all hours the agent is disconnected during k load sheds, where $\delta_i(s)$ is the comfort cost of the agent during the hour of shedding event s. The utilitarian objective is adapted as the addition of aggregated discomfort for n agents, $\sum_{i=1}^{n} \delta_i^*$, where $\delta_i^* = \sum_{s=1}^{k} \delta_i(s)$. The egalitarian objective is adapted as the highest individual comfort cost to the system (or highest aggregated negative utility), $e_{\delta}^{-} = \max_i\{\delta_i^*\}$. Finally, the envy-freeness objective is adapted as the maximum difference between the aggregated discomfort of all pairs of agents (or maximum difference between aggregated negative utilities), $e_{\delta} = \max_{i,j}\{|\delta_i^* - \delta_j^*|\}$. Table 1 compares the utilitarian, egalitarian and envy-freeness objectives, based on comfort costs.

In terms of the number of times agents are disconnected, the utilitarian objective is adopted as $u_N^{-} = \sum_{i=1}^{n} N_i$, where N_i is the aggregated number of times each agent is disconnected. Whereas, the egalitarian objective is adopted as $e_N^{-} = \max_i\{N_i\}$, while the envy-freeness objective is adopted as $e_N = \max_{i,j}\{|N_i - N_j|\}$. Table 2 compares the utilitarian, egalitarian and envy-freeness objectives, based on number of disconnections.

Table 2: Comparing economic fairness objectives, based on number of disconnections

Heuristic	Utilitarian	Egalitarian	Envy-freeness
Grouper	80501	325	184
Consumption-Sorter	**77031**	**208**	**1**
Random-Selector	88866	239	**1**
Cost-Sorter	101165	264	**1**

All four heuristics work by selecting agents one after the other, until the sum of consumption of the selected agents is enough to offset the deficit, thereby shedding enough load to offset the deficit, yet minimizing the difference between the deficit and the load shed. However, in terms of the proportion of the population of agents disconnected and the ratio of number of agents disconnected to every kWh shed during shedding events, all four heuristics perform differently.

4 CONCLUSIONS

This paper proposed a new approach to load shedding, and presented four heuristic algorithms for shedding load at the household level. Some qualities of the algorithms can be adapted into designs that suit different environments, based on the desired objectives. They can also serve as a benchmark for designing load shedding algorithms in the future, and in designing solutions for allocating other scarce resources (e.g. water allocation problems addressed by [13]).

[2]Nigeria's energy situation is representative of challenges in developing countries.
[3](See http://www.holiday-weather.com/austin/averages/ and http://www.holiday-weather.com/lagos/averages/.

REFERENCES

[1] K. R. Ajao, O. A. Oladosu, and O. T. Popoola. 2011. Using HOMER Power Optimization Software for Cost Benefit Analysis of Hybrid-Solar Power Generation Relative to Utility Cost in Nigeria. *Academic Journal* 7 (2011), 96–102.

[2] Julius Quarshie Azasoo and Kwame Osei Boateng. 2015. A Retrofit Design Science Methodology for Smart Metering Design in Developing CountriesA Smart Retrofitted Meter for Developing Countries. *15th International Conference on Computational Science and Its Applications (ICCSA)* (2015), 1–7. https://doi.org/10.1109/ICCSA.2015.23

[3] Nnaemeka Vincent Emodi, Chinenye Comfort Emodi, Girish Panchakshara Murthy, and Adaeze Saratu Augusta Emodi. 2017. Energy policy for low carbon development in Nigeria: A LEAP model application. *Renewable and Sustainable Energy Reviews* 68 (2017), 247 – 261. https://doi.org/10.1016/j.rser.2016.09.118

[4] F.I. Ibitoye and A. Adenikinju. 2007. Future demand for electricity in Nigeria. *Applied Energy* 84, 5 (2007), 492 – 504. https://doi.org/10.1016/j.apenergy.2006.09.011

[5] Eliel Keelson, Kwame Boateng, and Isaac Ghansah. 2014. A Smart Retrofitted Meter for Developing Countries. *International Journal of Computer Applications* 90, 5 (2014), 40–46. https://doi.org/10.5120/15573-4203

[6] João Leite, José Alferes, and Belopeta Mito. 2009. Resource Allocation with Answer-set Programming. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems - Volume 1 (AAMAS '09)*. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 649–656. http://dl.acm.org/citation.cfm?id=1558013.1558103

[7] Maxwell Umunna Nwachukwu, Nnena Flora Ezedinma, and Uloma Jiburum. 2014. Comparative Analysis of Electricity Consumption among Residential, Commercial and Industrial Sectors of the NigeriaâĂŹs Economy. *Journal of Energy Technologies and Policy* (2014).

[8] J. O. Oji, N. Idusuyi, T. O. Aliu, M. O. Petinrin, O. A. Odejobi, and A. R. Adetunji. 2012. Utilization of Solar Energy for Power Generation in Nigeria. *International Journal of Energy Engineering* 2 (2012), 54 – 59. https://doi.org/10.5923/j.ijee.20120202.07

[9] Oliver Parson, Grant Fisher, April Hersey, Nipun Batra, Jack Kelly, Amarjeet Singh, William Knottenbelt, and Alex Rogers. 2015. Dataport and NILMTK: a building data set designed for non-intrusive load monitoring. (September 2015). https://eprints.soton.ac.uk/381304/

[10] Oshevire Patrick, Oladimeji Tolulolope, and Onohaebi Sunny. 2013. Smart Grid Technology and Its Possible Applications to the Nigeria 330 kV Power System. *Smart Grid and Renewable Energy* 2013, August (2013), 391–397. https://doi.org/10.4236/sgre.2013.45045

[11] Claire Salmon and Jeremy Tanguy. 2016. Rural Electrification and Household Labor Supply: Evidence from Nigeria. *World Development* 82 (2016), 48 – 68. https://doi.org/10.1016/j.worlddev.2016.01.016

[12] José M. Vidal. 2009. *Fundamentals of Multiagent Systems with NetLogo Examples*. Unpublished. http://www.multiagent.com http://www.multiagent.com.

[13] Wan zhen Song, Yuan Yuan, Yun zhong Jiang, Xiao hui Lei, and Dong cai Shu. 2016. Rule-based water resource allocation in the Central Guizhou Province, China. *Ecological Engineering* 87, Supplement C (2016), 194 – 202. https://doi.org/10.1016/j.ecoleng.2015.11.051