Solving the Fair Electric Load Shedding Problem in Developing Countries

JAAMAS Track

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ABSTRACT

Many developing countries frequently resort to disconnecting large parts of their power grid from supply (i.e., load shedding), often due to limitations in their generation capacity. Some homes suffer more than others because fairness is not taken into due consideration during load shedding. In this paper, we briefly discuss and evaluate a number of solutions which mitigate against unfairness and improve efficiency in load shedding.

KEYWORDS

Load shedding; Fairness; Constrained optimisation

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1 INTRODUCTION

Load shedding is common in many developing countries. This is often so because they do not generate enough electricity to meet the demand on their power systems.[1] During load shedding, parts of the power system are disconnected from supply in order to maintain a balance between demand and supply. While this reduces the strain on the system and prevents it from collapsing, it also leaves homes within disconnected parts without electricity. Furthermore, some homes bear the brunt of load shedding because standard load shedding techniques do not focus on fairly allocating electricity to homes, as much as they do on maintaining a demand-supply balance.

Against this background, this paper presents a summary of the household-level load shedding solutions in [6]. These solutions consider the heterogeneous electricity needs of homes and uses these to fairly connect homes to supply. They build on existing research in resource allocation,[2] and assume the availability of purpose-built (for developing countries) smart retrofits for different kinds of electric meters [3]. They also rely on homes being modelled as inactive agents (as summarised in Section 2), examples of which represent price-taking buyers or sellers in marketplaces.

[1]For example, Nigeria generates under 8 MW for a population of over 170 million people [7].

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2 MODELLING HOUSEHOLD-LEVEL LOAD SHEDDING FOR DEVELOPING COUNTRIES

The load shedding solutions herein are developed for homes. However, the benefit of these solutions are overarching, as the residential sector constitutes a large percentage of the demand on the grid. Such is the case in Nigeria (which we use as a case study), where the residential sector accounts for 51.3% of grid demand [4].

2.1 Simulation of Household Consumption Data

Due to the unavailability of a relevant real-world household-level electricity consumption dataset for multiple homes in developing countries, a verifiable, authenticated, readily available household consumption data of homes in the USA was downloaded (from Pecan Street Inc's Dataport)[3]. This was then adapted into one representative of Nigeria. Dataport was selected as a resource because it contains desegregated (i.e., appliance-level) consumption data for multiple homes over years, and for locations where the average temperature during the warmest months are similar to those in Nigeria. The dataset was adapted by collecting the consumption data of appliances common in Nigeria during periods when the external temperature is warmest, and aggregating these to make up the electricity consumed in homes.

2.2 Modelling Homes as Agents

From the hourly consumption data for each home for up to four previous weeks[4] (say $C_i^{w=1}$ to $C_i^{w=4}$, where $C_i^w = (c_i^{t=1}, \dots, c_i^{t=168})$), a model of the consumption profile of each household i is computed

[2]A resource allocation problem is a fair division problem whose solution involves finding an allocation of limited resources between a number of interested entities, subject to the availability of the resource and how interested the entities are in the resource [1].

[3]Dataport is the largest provider of accessible disaggregated household energy consumption data [8].

[4]We consider weekly periods because the consumption pattern of a typical home will likely differ on different days of the week [2, 9] due to the activities of occupants, so

as a vector ζ_i , as in $\zeta_i = \big(\mathcal{N}(\mu_i^{t=1}, \sigma_i^{t=1}), \ldots, \mathcal{N}(\mu_i^{t=168}, \sigma_i^{t=168})\big)$, where ζ_i is the vector of the hourly consumption of i over the week, with the consumption for each hour drawn from a normal distribution of mean μ_i^t (i.e., $\mu_i^t = \sum_{w=1}^{4} c_i^{w,t}$) and variance σ_i^t (i.e., $\sigma_i^t = \big(\sum_{w=1}^{4}(c_i^{w,t} - \mu_i^t)^2\big)/4$).

Thereafter, ζ_i is normalized so that the consumption profiles of all homes fall within the range $(\epsilon, 1)$, where $\epsilon \in \mathbb{R}_{>0}$ is a very small number. This creates a vector of *comfort*, Δ_i as in $\Delta_i = \zeta_i / \max_t\{\zeta_i\} = \big(\delta_i^{t=1}, \ldots, \delta_i^{t=168}\big)$, where Δ_i is a vector of values $\delta_i^t \in \mathbb{R}_{>0}$. Consequently, Δ_i represents the preference i has for electricity during all hours in a week.

Being a mapping from consumption, this model creates a vector of utilities for each agent in terms of its electricity needs. In addition, the electricity needs of all agents become uniquely quantifiable and interpersonally comparable, without considering how much electricity the agents consume with respect to others.

2.3 The Fair Load Shedding Problem (FLSP)

The hourly estimated demand of each agent $\tilde{c}_i^t$ is derived[5] from the representative data by drawing from the normal distribution $\tilde{c}_i^t \sim \mathcal{N}(c_i^t, 0.05)$. The aggregated hourly estimated demand of the set of agents (I) is represented as the hourly load on the system, and is denoted as $l^t \in \mathbb{R}_{>0}$, where $l^t = \sum_{i=1}^{n} \tilde{c}_i^t$. Similarly, the hourly estimated supply capacity available for meeting the demand of agents in I is represented as $g^t \in \mathbb{R}_{>0}$. The value of g^t for each day ahead is then taken as the average of the sum of hourly household consumption estimates for that day (i.e., $g^t = (\sum_{t=1}^{24} \sum_{i=1}^{n} \tilde{c}_i^t)/24$).

Now, in a developing country, it is often the case that l^t is greater than g^t. In this event, there is a deficit on the system and load shedding becomes necessary to maintain a balance between l^t and g^t. In executing load shedding, a piece-wise variable Λ_i^t is defined to take the value 1 if i is connected to electricity at t, and 0 otherwise.

3 LOAD SHEDDING SOLUTIONS

The solutions herein are based on other assumptions that household consumption estimates may be computed, that there is enough spinning reserve to cater for errors in computing these estimates, and that the vector of comfort is independent of load shedding events.[6]

A first set of heuristic solutions (see [5]) comprises of (1) the Grouper Algorithm which disconnects the group of agents that has suffered the least number of disconnections over time,[7] (2) the Consumption-Sorter Algorithm which uses a round-robin technique to disconnect individual agents from supply based on their consumption, (3) the Random-Selector Algorithm which uses a round-robin technique to disconnect agents from supply while being agnostic to their consumption, and (4) the Cost-Sorter Algorithm which uses a round-robin technique to disconnect individual agents from supply based on their comfort.

A second set of Multiple Knapsack Problem (MKP) based solutions are the Comfort Model which maximizes the comfort objective (as in max $\sum_{t=1}^{p} \sum_{i=1}^{n} \delta_i^t \Lambda_i^t$), and the Supply Model which maximizes the supply objective (as in max $\sum_{t=1}^{p} \sum_{i=1}^{n} \tilde{c}_i^t \Lambda_i^t$). They both do so based on the constraints that (1) demand is never higher than supply (as in $\sum_{i=1}^{n} \tilde{c}_i^t \Lambda_i^t \leq g^t \ \forall\ t \in \{1, \ldots, p\}$), (2) all agents are connected to supply daily for a number of hours as equal as possible (as in $\beta_2 \geq \sum_{t=1}^{p} \Lambda_i^t \geq \beta_1 \ \forall\ i \in I$), (3) every agent is delivered as much comfort as possible (as in $\sum_{t=1}^{p} \delta_i^t \Lambda_i^t \geq \beta_3 \ \forall\ i \in I$), and (4) every agent is supplied as much electricity as possible to meet its demand (as in $\sum_{t=1}^{p} \tilde{c}_i^t \Lambda_i^t \geq \beta_4 \ \forall\ i \in I$). Note that $p = 24$.

4 PERFORMANCE EVALUATION

We used the utilitarian, egalitarian and envy-freeness social welfare metrics in evaluating all solutions within three primary experiments. In the first experiment, the solutions were evaluated in terms of how long they connected agents to supply individually (based on the egalitarian and envy-freeness metrics) and collectively (based on the utilitarian metric) on the average. In the second, they were evaluated in terms of the comfort they delivered to agents individually and collectively on the average. Lastly, they were evaluated in terms of the electricity they supplied to agents individually and collectively on the average. Following these, the MKP solutions were found to connect more agents to supply, deliver more comfort to agents, and supply more electricity to agents on the average, both individually and collectively.

In another experiment, the solutions were evaluated in terms of the excess load they disconnected from supply during load shedding. The MKP solutions were found to be more efficient in this regard, as they disconnected less excess load than the heuristics. They were also found to deliver more comfort and electricity to each agent on the average in other experiments. In order to see how our solutions perform when estimates of demand are poor, we evaluated them under different levels of uncertainty (by increasing σ_i^t) and found that though they performed erratically when estimates of demand become poorer, their average results did not greatly differ.

Thereafter, we used our solutions to implement the FLSPs with other datasets in order to show that they generalize within similar settings, and found them to perform in line with prior evaluations. Finally, we considered the time complexities of all our solutions within which the heuristics and MKP solutions appeared to solve in exponential and linear time respectively with respect to the population of agents.

It is noteworthy that all of the above experiments were run repeatedly (up to nine times each), being the reason why the performances of the solutions evaluated on the average.

5 CONCLUSIONS

This paper presented a summary on the solutions which were developed to enable fairer and more efficient load shedding. The solutions were evaluated under a number of experiments, from which the constrained optimisation (i.e., MKP) solutions were found to produce results which Pareto dominated others. When taken together, the solutions herein establish a set of benchmarks for fair load shedding schemes. They also provide insights which may be used within other settings to develop fair allocation solutions for scarce resources.

that it becomes necessary to consider the household's typical consumption pattern during each day of the week [9].

[5] It is necessary to compute estimates of demand when planning for load shedding.

[6] These assumptions are justified in [6].

[7] The Grouper Algorithm is designed to mimic the response of human operators to load shedding, albeit at the household level. Human operators would normally disconnect parts of the grid from supply until demand slightly falls below available capacity.

REFERENCES

[1] Yann Chevaleyre, Paul E Dunne, Ulle Endriss, Jerome Lang, Michel Lemaitre, Nicolas Maudet, Julian Padget, Steve Phelps, Juan A Rodrguez-Aguilar, and Paulo Sousa. 2006. Issues in Multiagent Resource Allocation. *Informatica* 30 (2006), 3—-31.

[2] Linh Phuong Catherine Do, Kuan-Heng Lin, and Peter Molnár. 2016. Electricity consumption modelling: A case of Germany. *Economic Modelling* 55, Supplement C (2016), 92 – 101. https://doi.org/10.1016/j.econmod.2016.02.010

[3] 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

[4] Maxwell Umunna Nwachukwu, Nnena Flora Ezedinma, and Uloma Jiburum. 2014. Comparative Analysis of Electricity Consumption among Residential, Commercial and Industrial Sectors of the Nigeria's Economy. *Journal of Energy Technologies and Policy* 4, 3 (2014), 7–13.

[5] Olabambo I. Oluwasuji, Obaid Malik, Jie Zhang, and Sarvapali D. Ramchurn. 2018. Algorithms for Fair Load Shedding in Developing Countries. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*. International Joint Conferences on Artificial Intelligence Organization, 1590–1596. https://doi.org/10.24963/ijcai.2018/220

[6] Olabambo Ifeoluwa Oluwasuji, Obaid Malik, Jie Zhang, and Sarvapali Dyanand Ramchurn. 2019. Solving the fair electric load shedding problem in developing countries. *Autonomous Agents and Multi-Agent Systems* 34, 1 (11 Dec 2019), 12. https://doi.org/10.1007/s10458-019-09428-8

[7] S.O. Oyedepo. 2012. Energy and sustainable development in Nigeria: the way forward. *Energ Sustain Soc* 2, 15 (2012), 1–17.

[8] 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/

[9] Ngoc Cuong Truong, Long Tran-Thanh, Enrico Costanza, and Sarvapali D. Ramchurn. 2013. Towards Appliance Usage Prediction for Home Energy Management. In *Proceedings of the Fourth International Conference on Future Energy Systems (e-Energy '13)*. ACM, New York, NY, USA, 287–288. https://doi.org/10.1145/2487166.2487210