Prepared by:
LEE Beng Sin PhD
bengsin.lee@sunseap.com

LIM Shun Xian
shunxian.lim@sunseap.com

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1. Case study Title and short description

Energy Intelligence: Development of an Energy Data Disaggregation Algorithm by applying Big Data Analytics and Machine Learning

Sunseap developed a proprietary energy monitoring solution, named Energy Intelligence (EI), that uses artificial intelligence (AI) / machine learning (ML) algorithm for energy disaggregation. The solution was deployed to a selected number of HDB flats in a HDB estate to monitor building common facilities energy consumption such as lifts, lightings, pumps, and others in real-time. Specifically, EI has demonstrated the possibility of a cost efficient and non-intrusive energy monitoring solution compared to traditional sub-metering solutions. Energy measurement errors were within 5% tolerance verified by a 3rd party test service. Energy monitoring will form the corner stone of tomorrow's smart energy solutions such as block-to-block energy sharing, building quality of supply, building smart nanogrid, to name a few.

2. Word document (max 2 pages) including the following points:

- What issue is being faced?

As the rate of global warming intensifies, it is imperative to work towards useful inventive solutions and the widespread of sustainable notions and tools that could help mitigate the slowdown of climate change. We see huge efforts carried out to meet the targets that Singapore has pledged to reduce our Emissions Intensity by 36% by 20304[i]. Having useful insights on electricity consumption is believed to be instrumental in reaching optimal or improving energy efficiency which is an important means to reducing carbon emissions, a culprit behind global warming and climate change. However, we realised that energy consumption is mostly presented in an aggregated manner which limits insights; the HDB, Town Councils and residents do not have access to disaggregated energy information.

To obtain a disaggregated load data, according to prevalent market practice, a sub-metering system, where a smart plug (USD50/pc5) or power meter must be installed on *each* major appliance in the building, has to be in place; long installation hours, high opportunity cost and hefty expenses. For this reason, the cost of traditional sub-metering is economically untenable for residential and commercial building because the tangible deterring high cost commonly outweighs the intangible concept of being sustainable to most people. This makes it difficult, if not impossible, for the formulation and implementation of any sound energy strategy. To illustrate, service and maintenance of equipment today are mostly done on a time-scheduled basis instead of a targeted basis, resulting in redundancy and wastage of resources.

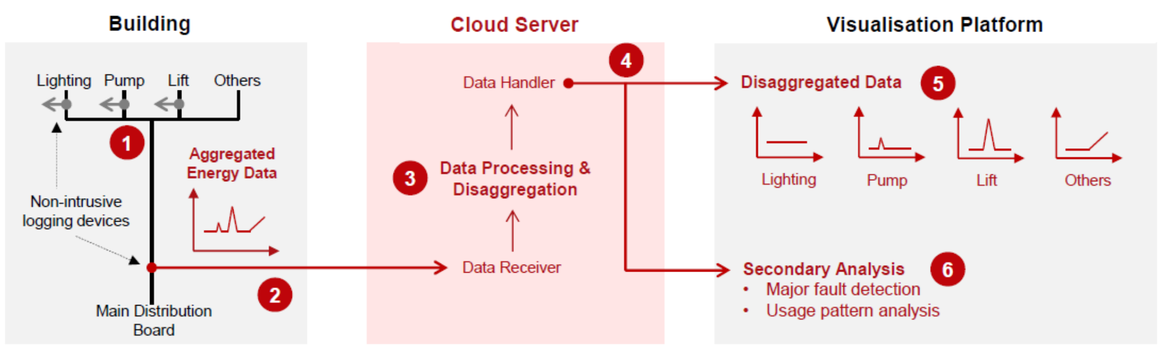
- What is the goal of doing the project?

Sunseap then investigates innovative and cost-effective methods to obtain disaggregated data. We resonated with the concept of the non-intrusive load monitoring (NILM) where a single point of power measurement at the main breaker level, combined with signal processing techniques, can provide information on power consumption at an equipment-specific level. This energy disaggregation technique relies on deep learning for extracting equipment-group level data from aggregate or the entire building energy signals without the need of any plug level sensors. It supports our project objective to allow end-users, namely the Town Councils and its Facility Managers, to make informed decisions on energy usage based on disaggregated energy information to improve energy efficiency.

- What solution was implemented?

We have developed a proprietary analytical algorithm that reads and disaggregate energy data for HDB common facilities, namely lifts, lightings, pumps, and others in real-time, based on a single point of data collection at the main switchboard. We were able to tap on machine learning algorithms, such as neural networks, to work out a more accurate way of energy data disaggregation which works at the fine time granularity right down to the second.

How it works:



1. Temporary logging of individual loads for machine learning via non-intrusive logging instruments.

2. Raw energy data is collected at the main distribution board.

3. Data is processed and disaggregated by an artificial intelligence algorithm.

4. Disaggregated data and analysis results are sent to a visualisation platform.

5. Energy data of individual electrical loads are displayed on the building management system platform.

6. Secondary analysis and status assessment of these loads can also be integrated with automatic response systems.

- Project Outcome - Did it work? Why, or why not?

We have performed an energy consumption test and verified by a 3rd party test service provider and observed that measurement errors were within 5% tolerance as illustrated below.

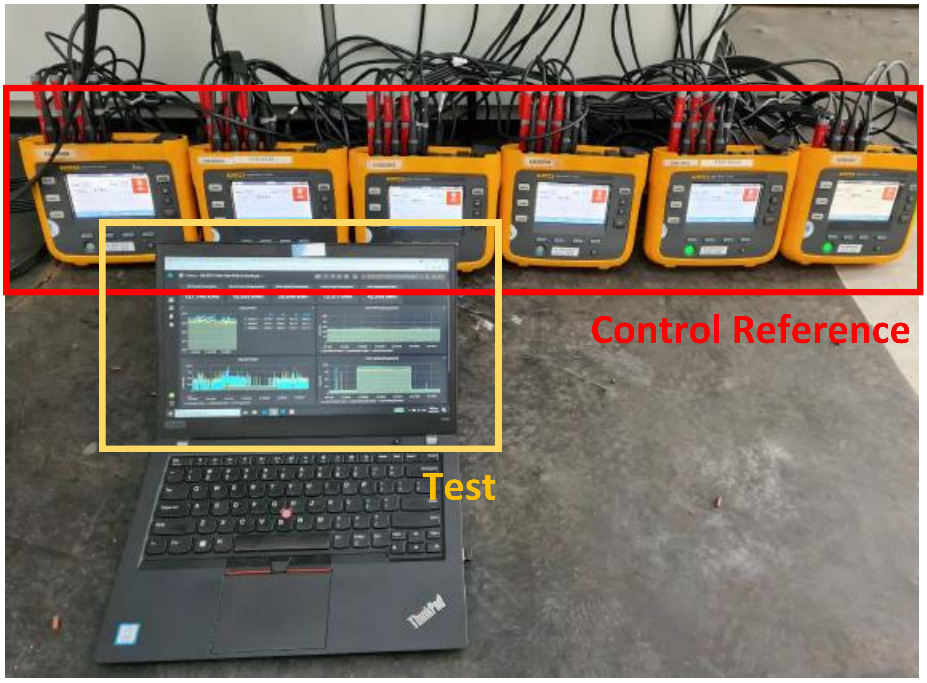


Table 1: Energy Consumption test

Model	Items	DUT (Energy Intelligence Methodology)						Unit	Tolerance (+/-5%)	Error%	Results
		Reference readings			Dashboard readings						
		2021.06.10 @2.10PM	2021.06.11 @2.10PM	Total Energy	2021.06.10 @2.10PM	2021.06.11 @2.10PM	Total Energy				
EIM	Lift A	1.04	20.94	42.16	42.30	82.53	40.22	Kwh	5	-4.59	P
	Lift B	0.71	22.97								
	Booster Pump	0.58	18.36	17.78	18.56	35.83	17.27	Kwh	5	-2.88	P
	Transfer Pump	0.34	13.90	13.56	13.33	26.62	13.29	Kwh	5	-1.96	P
	Public Lighting	0.21	35.12	34.91	35.75	70.88	35.13	Kwh	5	0.63	P

[i] Iau, J. (2019, December 26). New standards to boost energy efficiency. Retrieved from https://www.straitstimes.com/singapore/new-standards-to-boost-energy-efficiency