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A Novel Approach for Detecting Technical and Non-technical Losses in the Smart Grid: A Machine Learning-based Complex System Model.

Retaj Alsulami, Saad Aldoihi, Motaz Alfarraj

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Statement of the Problem

Nowadays, electricity is distributed via the **Smart Grid** (SG). The SG (Figure 1) is an electricity network enabling a two-way flow of electricity and data with digital communications technology (Figure 2). However, not all generated electricity in the SG is brought to end-consumers as **17%** of it is lost in **transmission** lines, and **50%** is lost in **distribution** lines. These losses are categorized as **Technical losses** (TL) or **Nontechnical losses** (NTL). TL are losses caused by action internal to the power system, whereas NTL are losses caused by action external to the power system.

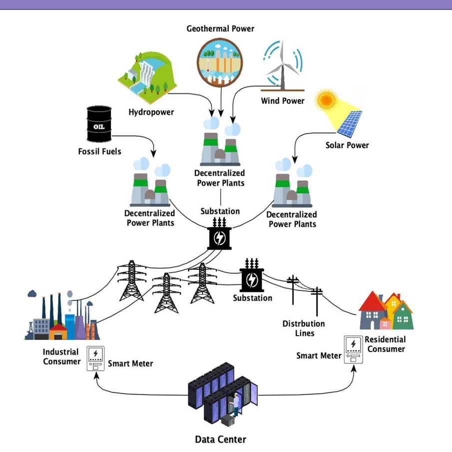


Fig.1. An Illustration of a Smart Grid

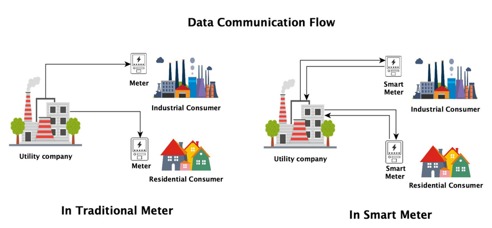


Fig.2. Data Communication Flow

Purpose of the Study

This research aims to devise an **industry-wide** and a **cohesive** solution to the problem of technical and nontechnical loss in the Smart Grid by providing utilities with a system to better understand their grids' technicalities and observe when loss is happening on their networks. Ensuring efficient use of energy. Ultimately, contributing to environmental conservation and economic stability.

Background

In [2-3], software-based solutions (figure 3) for detecting technical and nontechnical losses had two limitations:

- They are unable of cohesively detecting technical and nontechnical losses in the Smart Grid. They either detected nontechnical loss or technical losses but not both.
- They are unable of utterly sustaining the complexity and number of stakeholders involved in computation.

Fair to say, the industry is not equipped with an applicable solution to overcome technical and nontechnical losses.

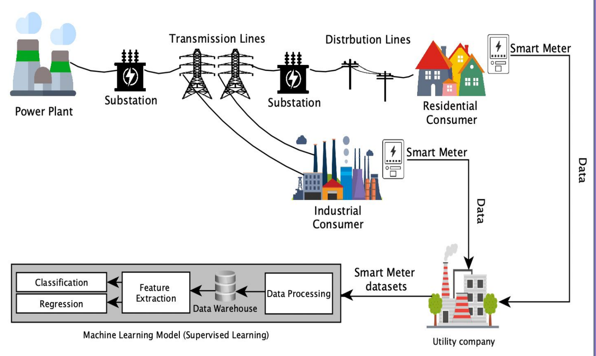


Fig.3. Software-based solutions for detecting power losses in the Smart Grid

Hypothesis

System model will cohesively detect and quantify technical and nontechnical losses in the Smart via the utilization of Model-based Systems Engineering methodologies, Machine Learning algorithms, and Smart Meter data.

Variables

- Machine Learning 1.0
  - Independent
    - Customer ID
    - Reading Datetime
    - General kWh Supply
  - Dependent
    - Nontechnical Loss
- Machine Learning 2.0
  - Independent
    - Power Factor
    - Peak Demand
    - Load/loss Demand
    - Cable Length
  - Dependent
    - Technical Loss

Methods

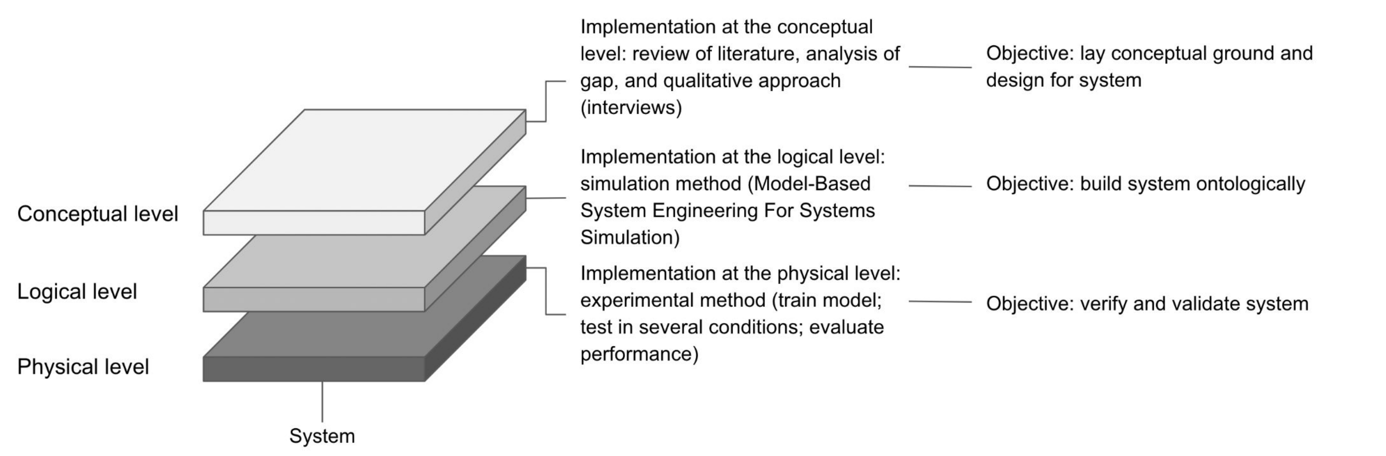


Fig.4. System's mixed methods of implementation at conceptual, logical, and physical levels

Procedures:

1. System modeling (logical implementation):
   - Mathematical modeling
   - Data modeling
2. Machine Learning trials (physical implementation)
   - Data collection: from papers and online datasets.
   - Data preparation: done by visualization, dimensionality reduction, balance, separation, pre-process (normalization, duplicates elimination, error correction).
   - Model training and evaluating: done by Python Sklearn.

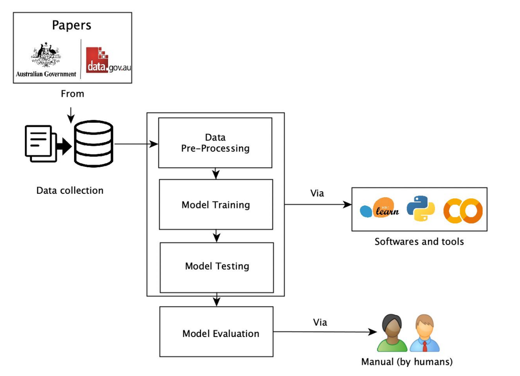


Fig.5. Design of Machine Learning model trials

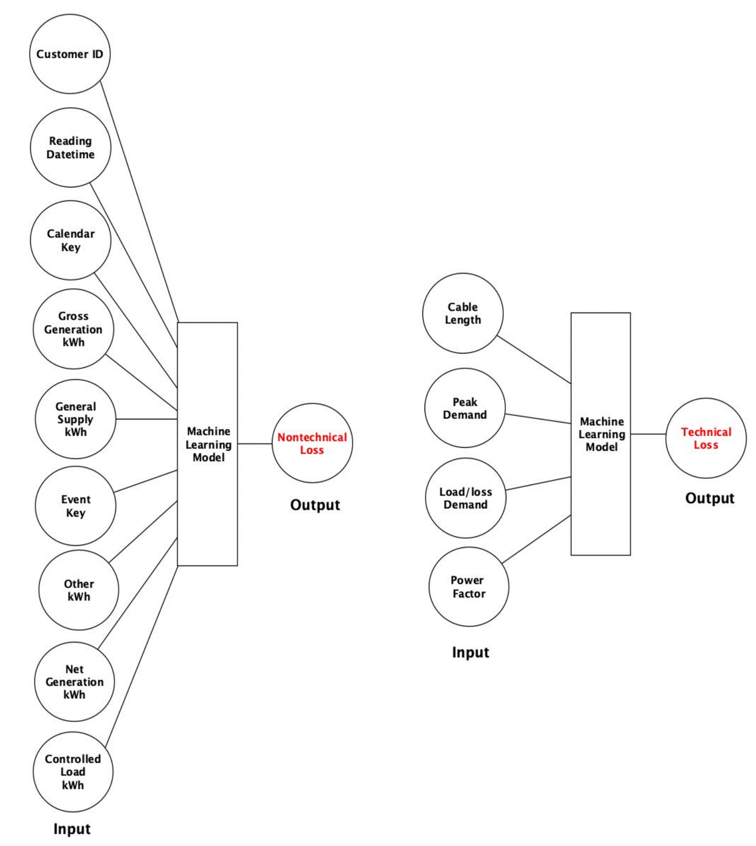


Fig.6. Inputs and Outputs of Machine Learning Model within the System

Data, Graphs, and Analysis

Logical implementation

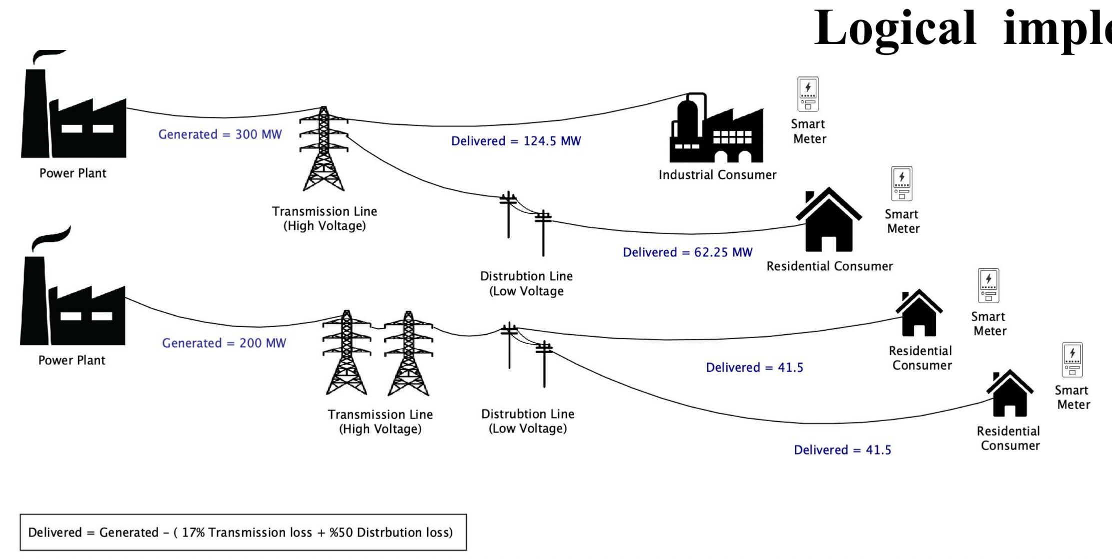


Fig.7. Layer one: observation of power losses

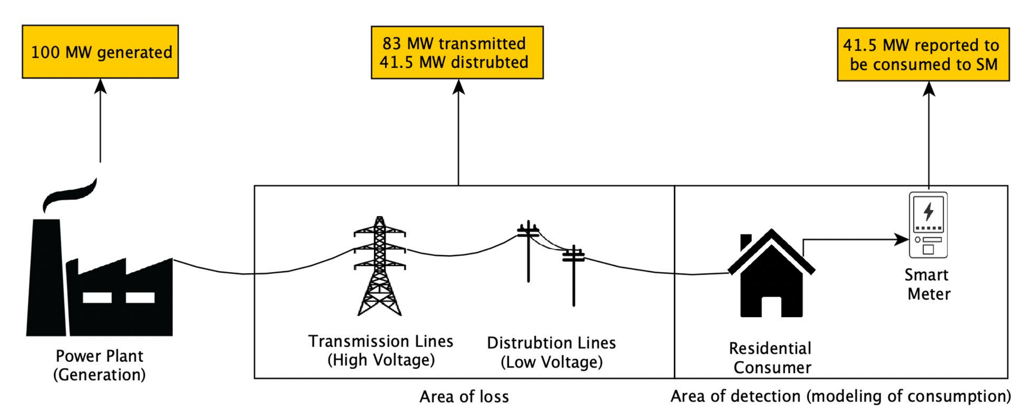


Fig.8. Layer one: a closer look at location of losses

Layer one, triggering of event:

1. Conditional mathematical modeling (if x =>0 , where x is sent kWh from the plants and 0 is calculated to be consumed via the smart meter).
2. When x < 0 (gate: are there losses or not?).
3. If yes, the event is triggered. If not, stay in the loop.

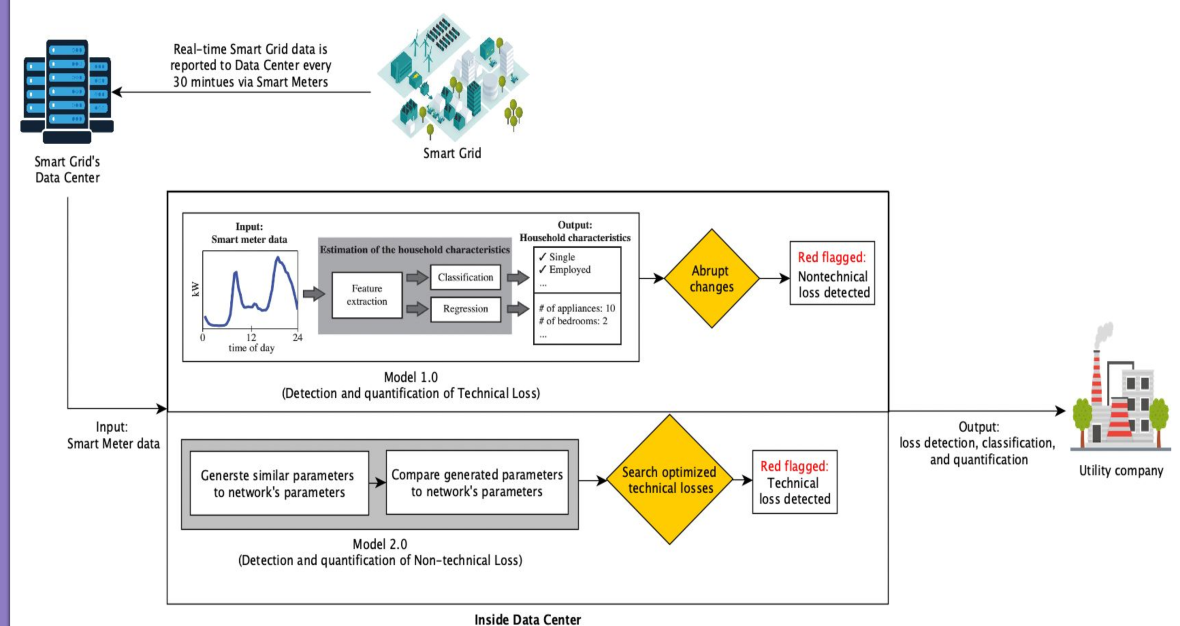


Fig.9. Layer two: modeling of power losses

Layer two, multi-dimensionality and classification:
Once the output (end of loop) of layer one is received, another loop is triggered (layer two: machine learning algorithms). In this loop, the system will evaluate the network, search the network for the optimized nontechnical losses based on predefined parameters and then find technical losses. This will be done through Artificial Neural Networks as they are found the best method in the literature.

Physical implementation

Technical loss detection

TABLE 1. Case Study of Distribution Network and Investigated Features for Technical Loss Detection

Monthly Incoming Units from Transmission individual feeders [MWhr]	28,800
System Peak Demand [MW]	80
Total No of 33 kV Feeders	7
Total No of 33/11 kV Transformers	16
Total No of 11 kV Feeders kV Feeders	52
Total No of 11/0.4 kV Transformers	500
Ratio of OH to UG LV Network	90% OH, 10%UG

Nontechnical loss detection

TABLE 2. Investigated Features of Online Dataset for Nontechnical Loss Detection

Customer ID	Reading Datetime	Calendar key
Event key	Gross Generation kWh	General Supply kWh
Controlled Load kWh	Net Generation kWh	Other kWh

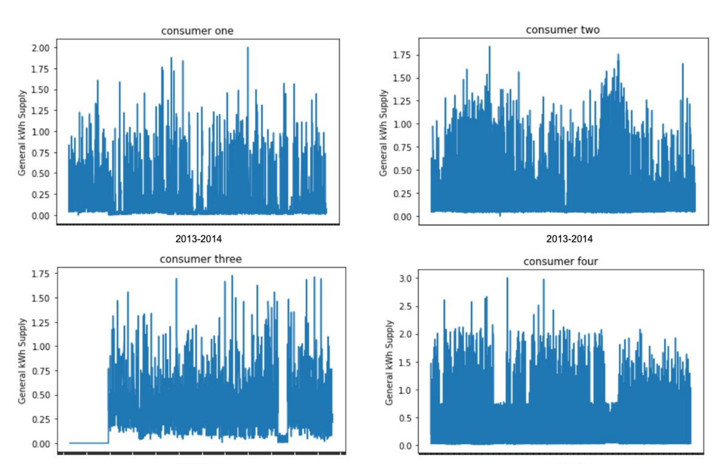


Figure. 10. Yearly Consumption of Four Residential Consumers on One Distribution Network. Data Was Collected from 2013 to 2014.

Graphs above showcase yearly consumption of four residential consumers on one network. This data can be modeled via Machine Learning to understand users' pattern and locate nontechnical losses.

Discussions

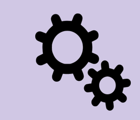
Because of the lack of data sharing and control rules, most studies used Synthetic Data (unreal/artificial data). The author of research recommends utilities to share authentic data to stimulate academic and scientific work on the issue. This data will help develop comprehensive tools for detecting technical and non-technical losses in the Smart Grid.

Results

A Novel Method

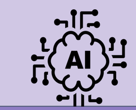
A novel cohesive approach is introduced. This approach is based on Model-based Systems Engineering methodologies, Machine Learning models, and Smart Meter data. This approach was validated by three experts.

A System Design



A system design is introduced. The first two layers of the system have been validated through experts of the field whereas validation of the last layer within the system is in progress (Machine Learning models).

Machine Learning Models



Two Machine Learning models are introduced. These two models are located within the last layer of the system. Validation of these two models is still in progress.

Conclusion

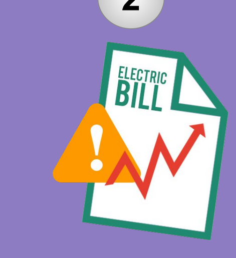
This research attempts to detect, classify, and quantify power losses located in transmission and distribution lines inside the Smart Grid via a multi-layered and multi-dimensional Machine Learning-based system model. The system is expected to productively detect, classify, and quantify losses. Ultimately, ensuring energy efficiency and management. Contributing to environmental conservation and economic stability.

Applications

1

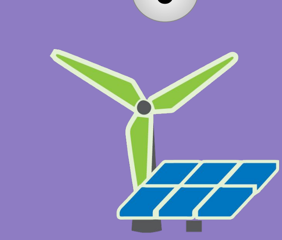
Smart cities (i.e. NEOM)

2



Utilities and electricity bills stabilization

3



Efficient harness of renewables

Future work

Short-term future work:
Since this system has been implemented in the conceptual and logical levels. It is anticipated to implement this system in the physical level through carrying out trials on the Machine Learning models within the system **by the end of February.**
Long-term future work:
To model a system more specifically fit to industry application; a derivative model that is more comprehensive for industry zones

References

[1] Buzau, M. M., Tejedor-Aguilera, J., Cruz-Romero, P., & Gómez-Expósito, A. (2018). Detection of non-technical losses using smart meter data and supervised learning. IEEE Transactions on Smart Grid, 10(3), 2661-2670.
[2] Au, M. T., Anthony, T. M., Kamaruddin, N., Verayiah, R., Mustaffa, S. A. S., & Yusoff, M. (2008, December). A simplified approach in estimating technical losses in distribution network based on load profile and feeder characteristics. In 2008 IEEE 2nd International Power and Energy Conference (pp. 1661-1665). IEEE.
[3] Ford, V., Siraj, A., & Eberle, W. (2014, December). Smart grid energy fraud detection using artificial neural networks. In 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG) (pp. 1-6). IEEE.