# Anthropomorphic and Accountable AI-Driven Power Generation and Distribution System

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***Abstract*—This paper propose human-centric AI-driven power grid distribution system (PGD) that dynamically allocates power to different clusters of buildings in a multiple complex environment using explainable cognition. The PGD system adopts Elastic Net regularization technique and SHAP method to achieve a cost-effective and lightweight interpretation of its prediction process with minimal prediction error of 28082 and coefficient of determination of -0.0032.**

***Index Terms*—anthropomorphic, energy distribution, explainable AI, regression, power.**

## I. Introduction

The Gumi Industrial Complex, South Korea, has reportedly suffered from inefficient power distribution due to outdated energy monitoring systems. With the growing complexity of modern energy grids, adaptable artificial intelligence (AI)-driven processes are crucial for efficient distribution. Anthropomorphism helps clarify AI decision-making, making systems more accountable, adaptive, and reliable. Traditional AI struggles with dispersed networks, fluctuating demands, and renewables due to reliance on static models and historical data, creating scalability issues [1]. Although federated learning improves decentralized processing, it faces challenges with data disparities and coordination, which lead to biased predictions and limited accountability [2]. This lack of transparency hinders trust and justification of AI decisions in high-accountability power systems [3].

Recent research has introduced various models to enhance energy consumption prediction and management. The ECP-LightGBM model, proposed by [4], combines LightGBM with SHAP (SHapley Additive exPlanations) to address machine learning's "black-box" issue, aiming for better prediction accuracy, transparency, and interpretability. However, it struggles with large-scale applications. Similarly, [5] developed a LightGBM-SHAP model to predict energy use and GHG emissions based on urban design and building features, achieving an $R^2$ of 0.8435, but it's less applicable to non-urban areas. [6] introduced an LSTM model with XAI-SHAP for high-accuracy forecasting, though it is complex to scale.

Integrating Explainable AI (xAI) into power distribution enhances cost-effectiveness and transparency. xAI allows energy systems to optimize and clarify allocation decisions, building trust by making logic traceable. xAI-driven models are lightweight and cost-efficient, ideal for resource-limited settings [6], supporting responsible management and reducing operational costs and waste.

This paper proposes a lightweight, cost-effective Power Grid Distribution (PGD)-AI system that dynamically manages energy distribution across the Gumi Industrial Complexes. Our system leverages anthropomorphic AI principles, simulating human-like decision-making and providing clear explanations for energy allocation. The system integrates xAI techniques to ensure accountability in power distribution, enabling users within these complexes to understand how decisions are made in real-time. Through this approach, we aim to bridge the gap between efficiency and transparency in energy management, offering a novel solution that is both adaptive and accountable.

## II. Methodology

The proposed AI-driven PGD system generates power centrally and distributes it intuitively to the different devices within the Gumi industrial complex based on pattern discovery on data that indicate varying consumption-demand levels and other associated feedback from the logic and inference engine, as shown in Fig. 1. The explainable module provides humans understandable details of what led to the prediction.

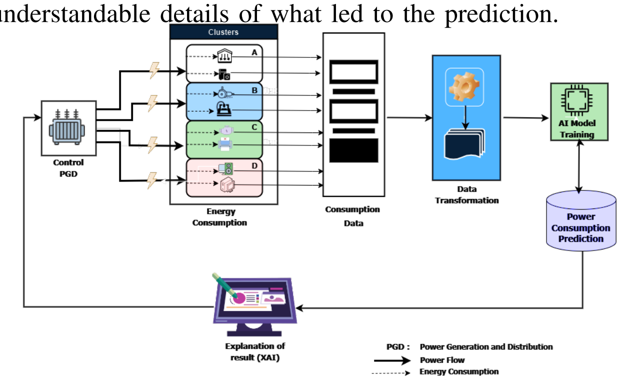


Fig. 1. Overview of the Proposed Power Grid Distribution System Design

The objective function of the PGD system is to optimize power distribution, $\mathtt{max}(\xi)$, by taking cognizance of the cluster of the consumption device, $\mathtt{max}(\mathtt{C})$ , the day of the week (date), $\mathtt{max}(\mathtt{D})$, and the period (hour, i.e. peak and low), $\mathtt{max}(\mathtt{T})$ that the device in each cluster is used as represented by the matrices.

$$\mathtt{C} = \begin{bmatrix} x_{11} & x_{12} & .. & x_{1n} \\ x_{21} & x_{22} & .. & x_{2n} \\ . & . & .. & . \\ x_{i1} & x_{i2} & .. & x_{in} \end{bmatrix} \qquad \mathtt{D} = \begin{bmatrix} d_{11} \\ d_{21} \\ . \\ d_{in} \end{bmatrix} \qquad \mathtt{T} = \begin{bmatrix} t_{11} \\ t_{21} \\ . \\ t_{in} \end{bmatrix}$$

Each row of the C-matrix represent a given cluster (say, A) with the elements representing the devices in that cluster mapped to the power consumed by the specific cluster on a specific day ($d$) and at a given period ($t$) of operation in the complex. This can be expressed by the regression line equation (1).

$$max(\xi) = \beta c_i + \beta d_i + \beta t_i + \epsilon \quad (1)$$

where $c_i, d_i,$ **and** $t_i$ are independent variables representing device name and cluster; date is used; and hour/period device is used while $\beta$ and $\epsilon$ are the coefficients of each variable and prediction errors.

To prevent overinterpretation by the AI model, account for nonlinear relationships between inputs, and perform adequate feature selection (while ensuring lightweight), we adopted the Elastic Net regularization (ENR) technique (a combination of L1 and L2 regression) using the Grid-Search Cross Validation algorithm as shown in equation (2) for data transformation and prediction.

$$\begin{aligned} L_{lasso}(\widehat{\beta}) &= \sum_{i=1}^{n}(y_i - {x^s}_i\widehat{\beta})^2 + \lambda \sum_{i=1}^{m} |\widehat{\beta}_i| \\ L_{hridge}(\widehat{\beta}) &= \sum_{i=1}^{n}(y_i - {x^s}_i\widehat{\beta})^2 + \lambda \sum_{i=1}^{m} w_i\widehat{\beta}_i^2 \end{aligned} \quad (2)$$

The Gumi industrial complex energy consumption dataset was used in this work. It has 727584 input data from 54 devices in 6 clusters with 4 features, namely device-id, date, period, and energy consumption. Dataset was divided into 80% training and 20% validation based on Pareto principle. Our proposed approach was compared with other AI algorithms using prediction efficiency and reliability metrics. Model local and global explaination was carried out using SHAP and other statistics. The simulation platform was Python environment using the Jupyter Notebook on a computer running Windows 10 with Intel(R) Core(TM) i5-8500 CPU @ 3.00GHz, 6Core(s), NVIDIA GeForce GT 1030, GPU CUDA:0 (Tesla K80, 11441.1875MB), and 36GB RAM.

## III. Result and Discussion

Table I summarizes the prediction performance of ENR against other AI- models for regression analysis.

TABLE I
SIMULATION AND IMPLEMENTATION PLATFORM

| **Model** | **Mean Squared Error (MSE)** | **R-squared ($R^2$)** |
|---|---|---|
| Multiple Linear (MLR) | 55928.15 | -0.9980 |
| Decision Tree (DT) | 5159436.55 | -183.3200 |
| Random Forest (RF) | 1789019.04 | -62.9129 |
| Extreme Boosting (XGB) | 55928.15 | -0.9980 |
| **Elastic Net (ENR)**<br>**✓Lasso Regression (L1)**<br>**✓Ridge Regression (L2)** | <br>**28082.88**<br>**28083.74** | <br>**-0.0032**<br>**-0.0032** |

With a best alpha value of 0.0037 for Lasso regression and 10.0 best alpha for Ridge regression, the ENR exhibited a superior power consumption prediction with a minimal error (MSE) of 28082.88 and a low coefficient of determination ($\mathbf{R^2}$) of -0.0032 better than other models. this validates that ENR is a better approach for forecasting and predicting nonlinear distribution of power grid in clusters.

Furthermore, the diagram in Fig. 2 explains that not all the features of power consumption data significantly impacts on the ENR prediction except features 1, 3, 32, 2, and 4.

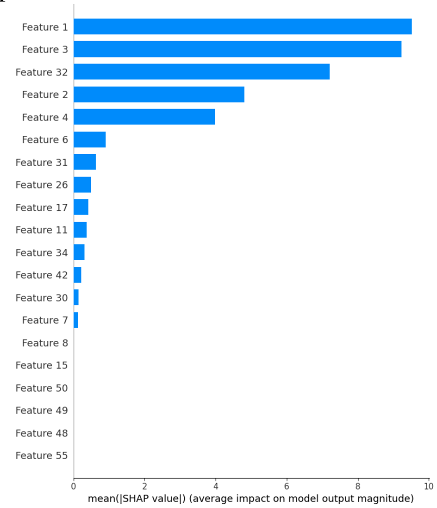


Fig. 2. xAI showing Average Impact of Data Features on Model Performance

## IV. Conclusion

This study proposed an AI-driven, responsible power grid distribution system that efficiently meets energy demands in diverse device clusters. Results indicate accurate, dynamic consumption prediction when installed on a micro-grid controller; future enhancements aim for increased robustness.

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