Energy Efficiency Optimization for Smart Homes

Presenters: **Group No:11**

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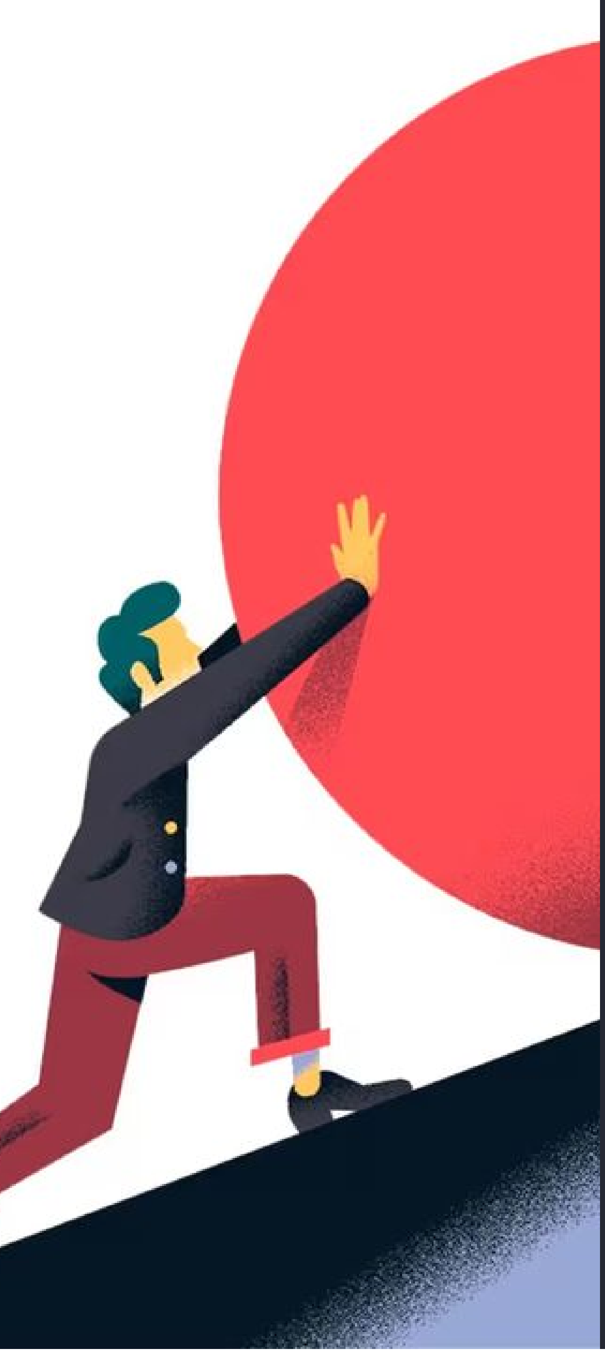
SCHEME OF PRESENTATION

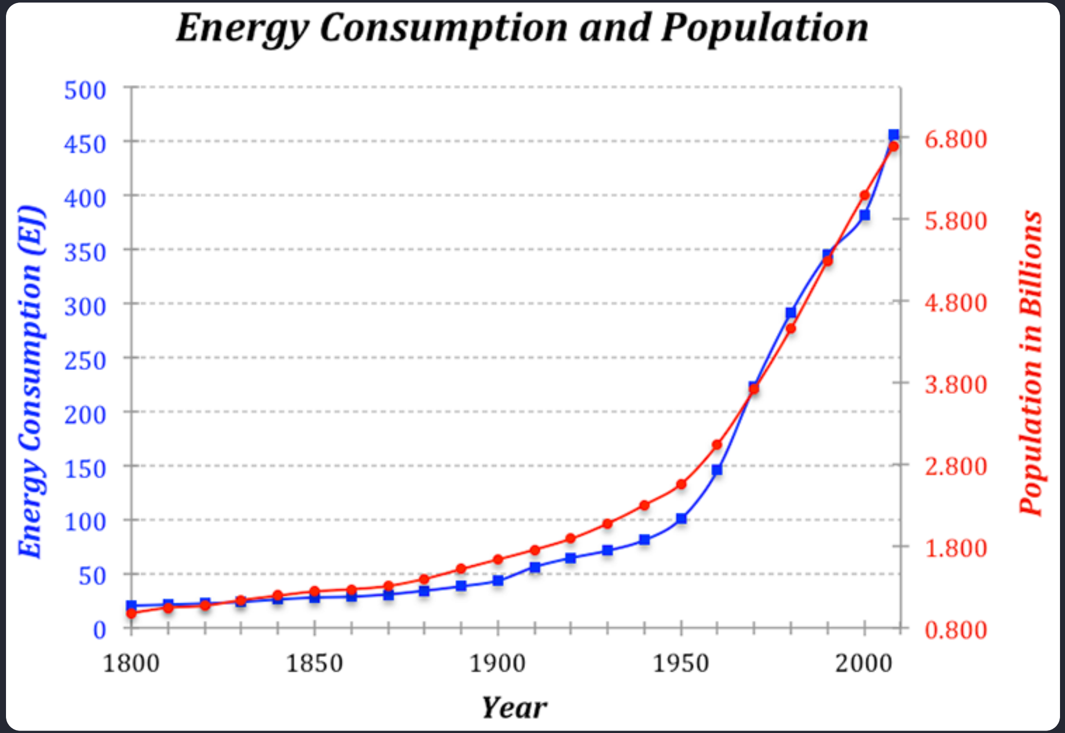
1. Problem Definition
2. Related Works and Future Direction
3. Data Mining Techniques Used in Project
4. Technical Details About Project
5. Experimental Results and Discussion

WHY did we choose Energy Efficiency Optimization for Smart Homes?

PROBLEMS AND CHALLENGES IN THE FIELD



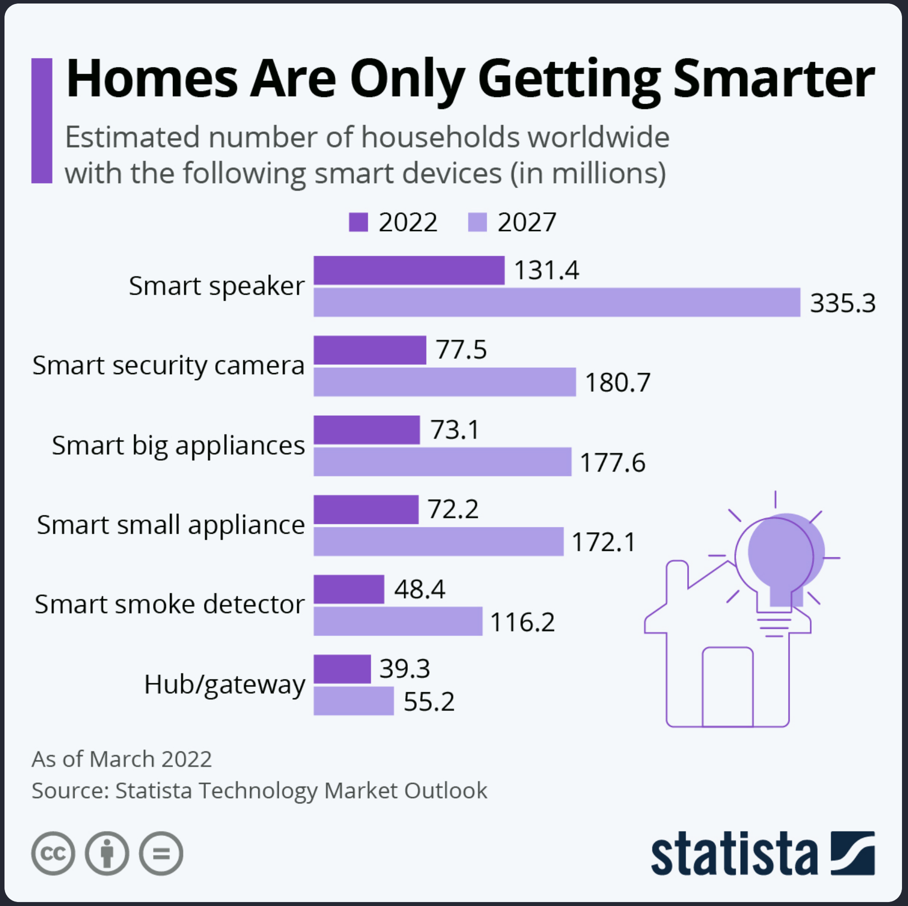
Energy consumption



Annual increasing in energy consumption remains a pressing issue, demanding urgent attention.

graph:https://www.e-education.psu.edu/earth104/node/1347

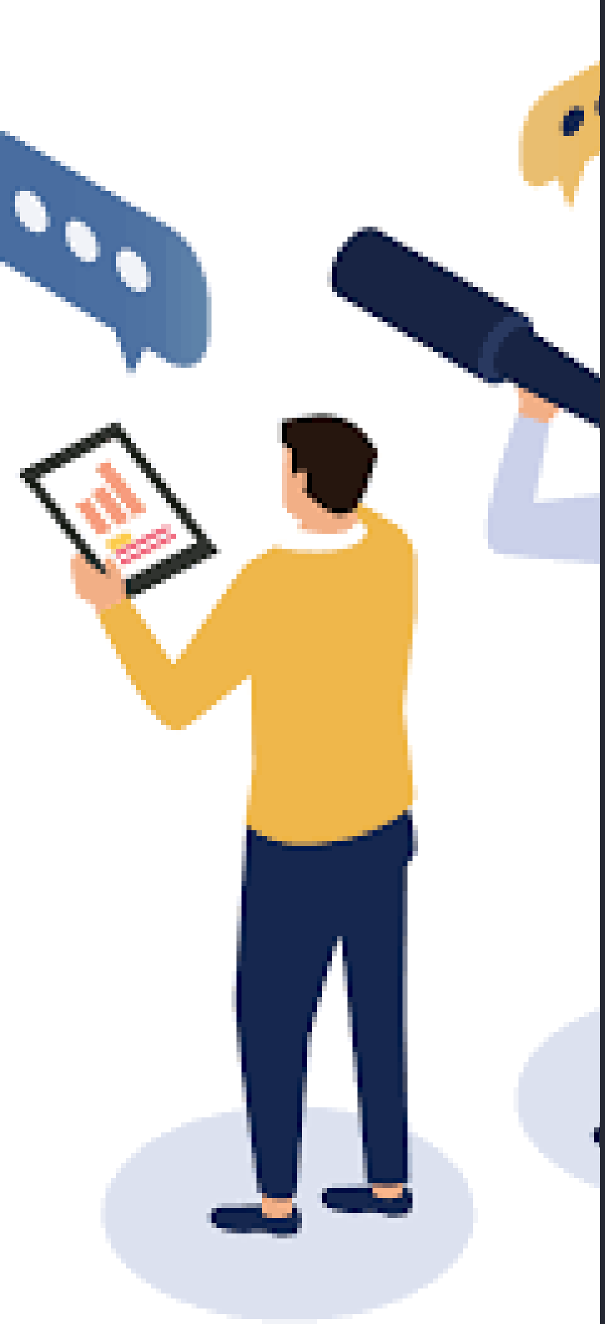
Increasing in Smart Home Devices



Smart home device adoption grows annually, showcasing an upward trend in integrating intelligent technology for modern living environments.

So There Are Two Choose for future: Producing More Energy or Consuming Less Energy.

Our project: aims to adjust the household's electricity consumption and optimize electricity plans to minimize the electricity consumption for smart homes.



Related works and Future Direction

Traditional Approaches: Early efforts in enhancing energy efficiency in smart homes primarily relied on rule-based and heuristic approaches. Researchers explored predefined rules and algorithms to schedule and control devices, but these methods often lacked adaptability to dynamic user behaviors and changing environmental conditions.

Machine Learning in Smart Homes: With the improvement of machine learning, researchers started integrating these techniques to enhance the adaptability and personalization of energy management systems. Various studies have employed supervised learning algorithms to predict user behaviors, enabling more accurate demand forecasting and load scheduling.

Related work coverage from the literature

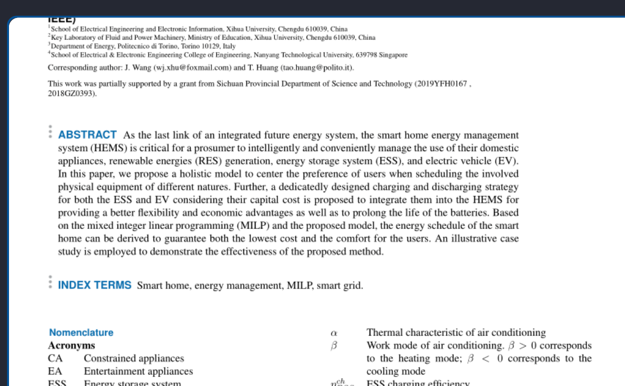
- A system has been developed by an Italian company to be used in Italy, providing energy savings ranging from 20% to 23%. This system is an automatic one and exhibits a high adaptability to new appliances and data arrangements.

Techprincess

Smart Home: come ridurre i consumi di energia e le...

Nice, azienda leader globale nell'Home Management Solution, s'impegna nello sviluppo di soluzioni Smart Home che...

- EES (Energy Storage System) and PEV (Plug-in Electric Vehicle) control strategy maximizes the utilization of renewable energy sources and flattens peak loads. Comparative studies indicate a potential 28% reduction in total costs with the implementation of these strategies.



IEEE)

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ABSTRACT As the last link of an integrated future energy system, the smart home energy management system (HEMS) is critical for a prosumer to intelligently and conveniently manage the use of their domestic appliances, renewable energies (RES) generation, energy storage system (ESS), and electric vehicle (EV). In this paper, we propose a holistic model to center the preference of users when scheduling the involved physical equipment of different natures. Further, a dedicatedly designed charging and discharging strategy for both the ESS and EV considering their capital cost is proposed to integrate them into the HEMS for providing a better flexibility and economic advantages as well as to prolong the life of the batteries. Based on the mixed integer linear programming (MILP) and the proposed model, the energy schedule of the smart home can be derived to guarantee both the lowest cost and the comfort for the users. An illustrative case study is employed to demonstrate the effectiveness of the proposed method.

INDEX TERMS Smart home, energy management, MILP, smart grid.

Nomenclature

Acronyms

CA Constrained appliances
EA Entertainment appliances
ESS Energy storage system
ESS2H ESS-to-Home

α Thermal characteristic of air conditioning
β Work mode of air conditioning. $\beta > 0$ corresponds to the heating mode; $\beta < 0$ corresponds to the cooling mode
η_{ESS}^{ch} ESS charging efficiency
η_{ESS}^{dis} ESS discharging efficiency

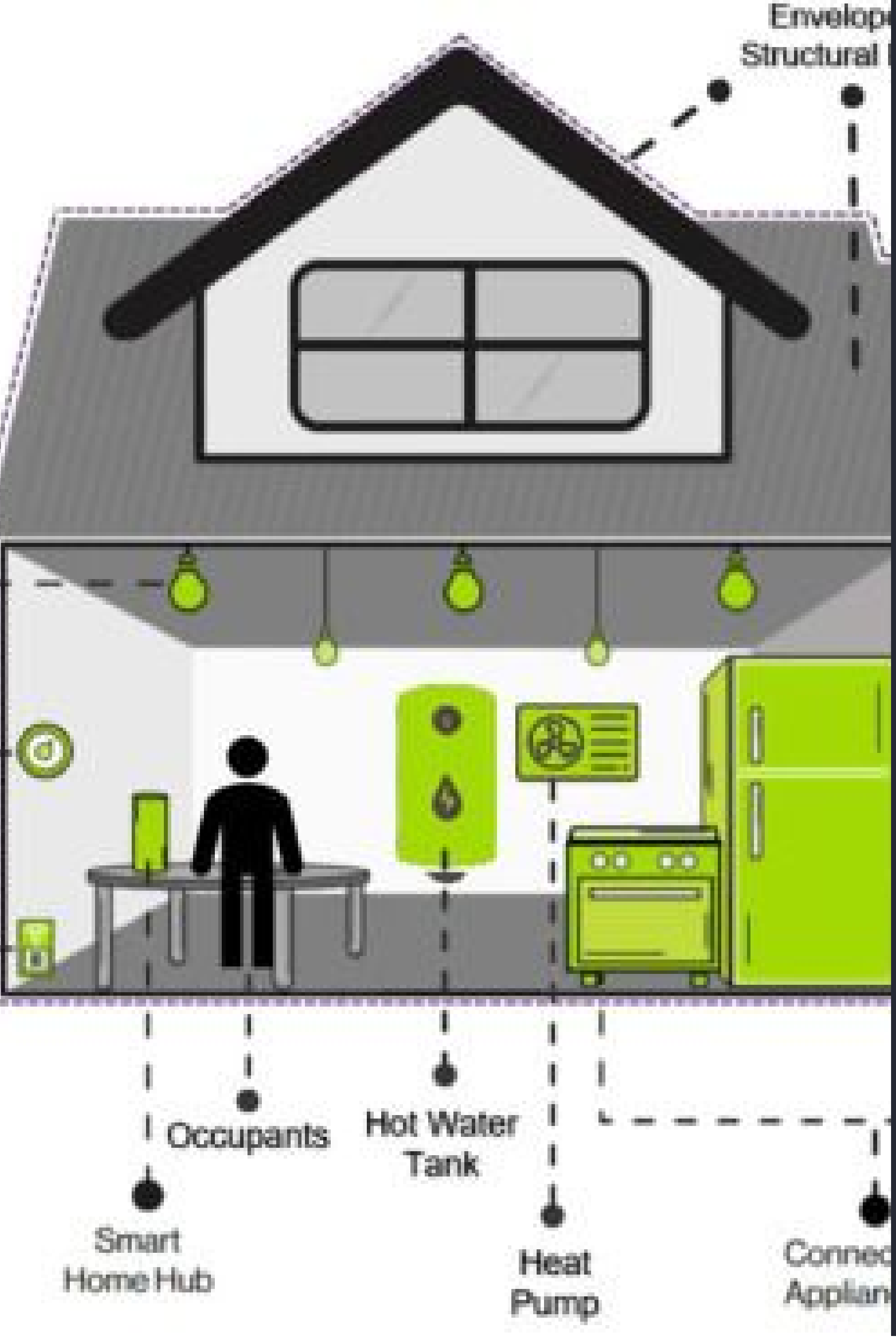
ResearchGate

(PDF) Smart Home Energy Management Optimizati...

PDF | As the last link of an integrated future energy system, the smart home energy management system (HEMS) is critic...

Future Directions

Finally , the literature emphasizes potential future directions for research in this domain, including the exploration of advanced machine learning techniques, the integration of renewable energy sources, and the development of more sophisticated algorithms to address emerging challenges in the ever-evolving landscape of smart home technology.



Technical Details About Project

- **The Cost Function**
- **Data Mining Techniques That Used in Project**
- **Inflexible Appliances**
- **Semi-Flexible Appliances**
- **Flexible Appliances**

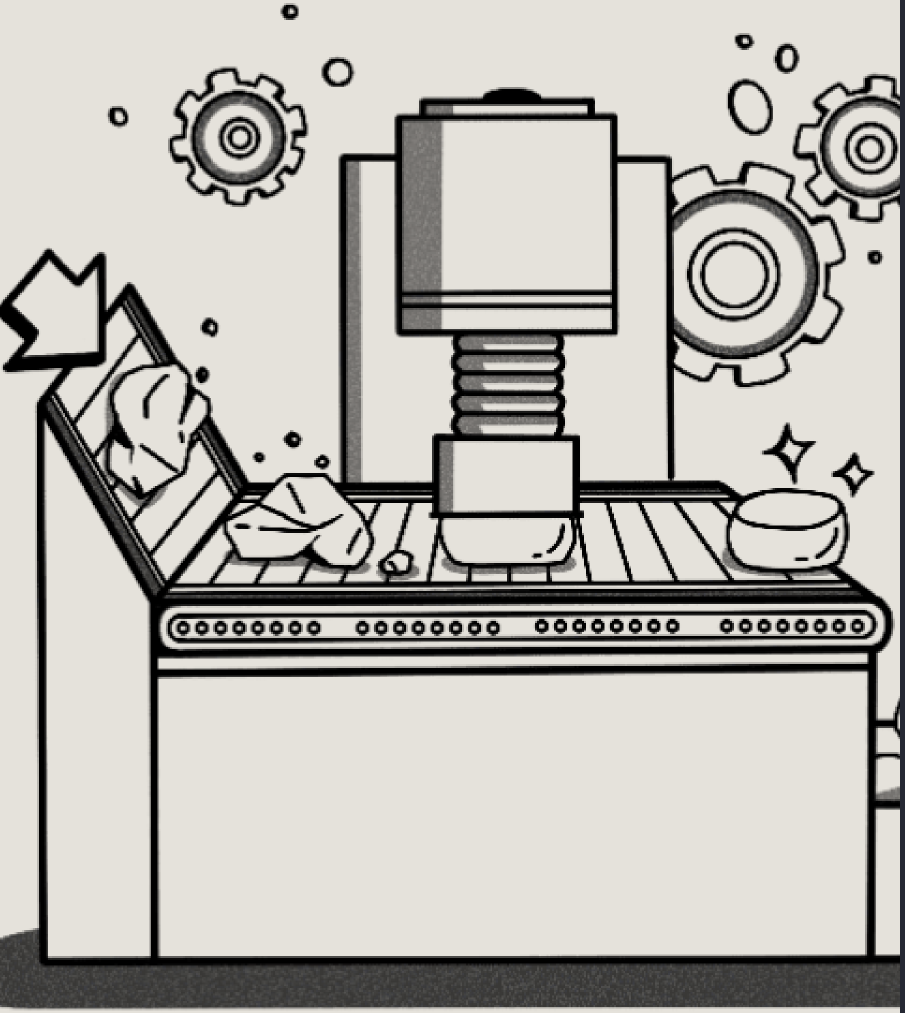
Calcuating Cost of Energy Usage

```
def calculateCost(list1):
  total = 0
  for i in range (len(list1)):
    if list1[i] <= 0.694:
      total +=list1[i] *0.149
    if 0.694 <list1[i] <= 1.389:
      total +=list1[i] *0.105
    if 1.389<list1[i] <= 2.778:
      total +=list1[i]* 0.132
  return  total

result_first=calculateCost(y_test)
result_first
```

Out: 113.81170

According to this link : **https://www.gotrhythm.com/blog/electricity-101/what-are-tiered-rate-energy-plans**, calculation cost funtion (hourly) must be like this.

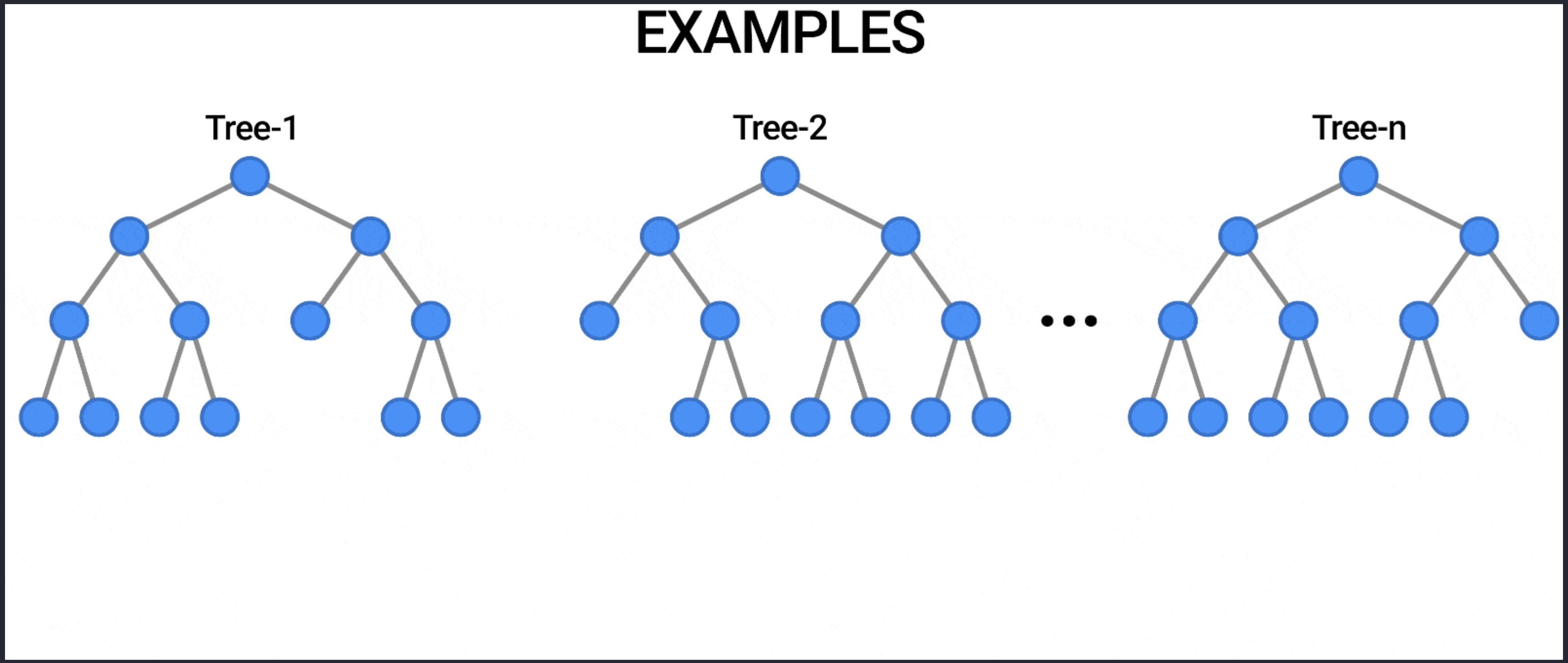


Data Mining Techniques That Used in Project

- Random Regressor
- Support Vector Machine(SVM)
- LSTM Neural Network
- Lineer Regression
- Xgboost

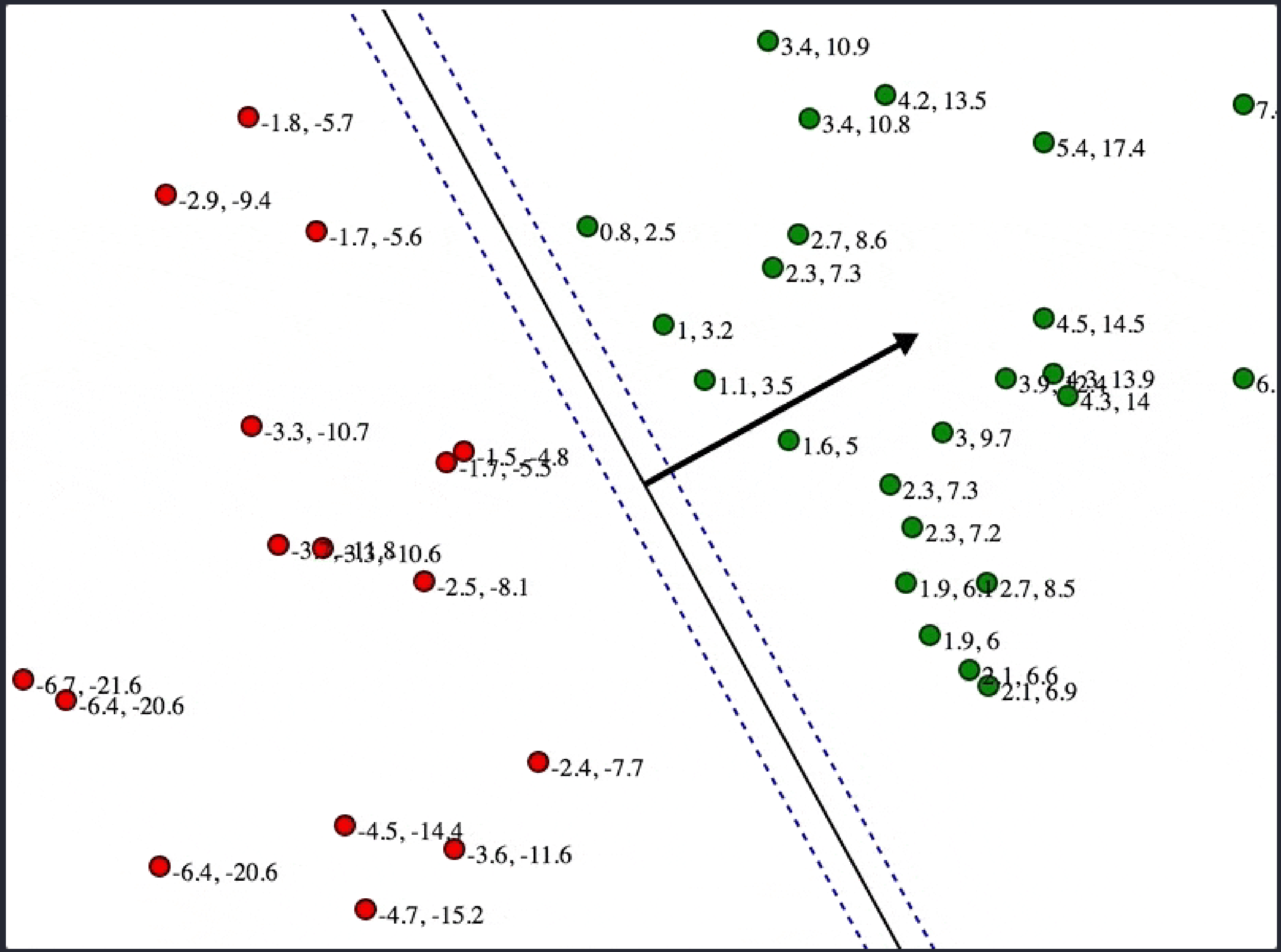
Random Forest Regressor

Random Forest is an ensemble machine learning technique. It constructs a multitude of decision trees during training and merges their outputs to enhance prediction accuracy and handle overfitting in diverse datasets



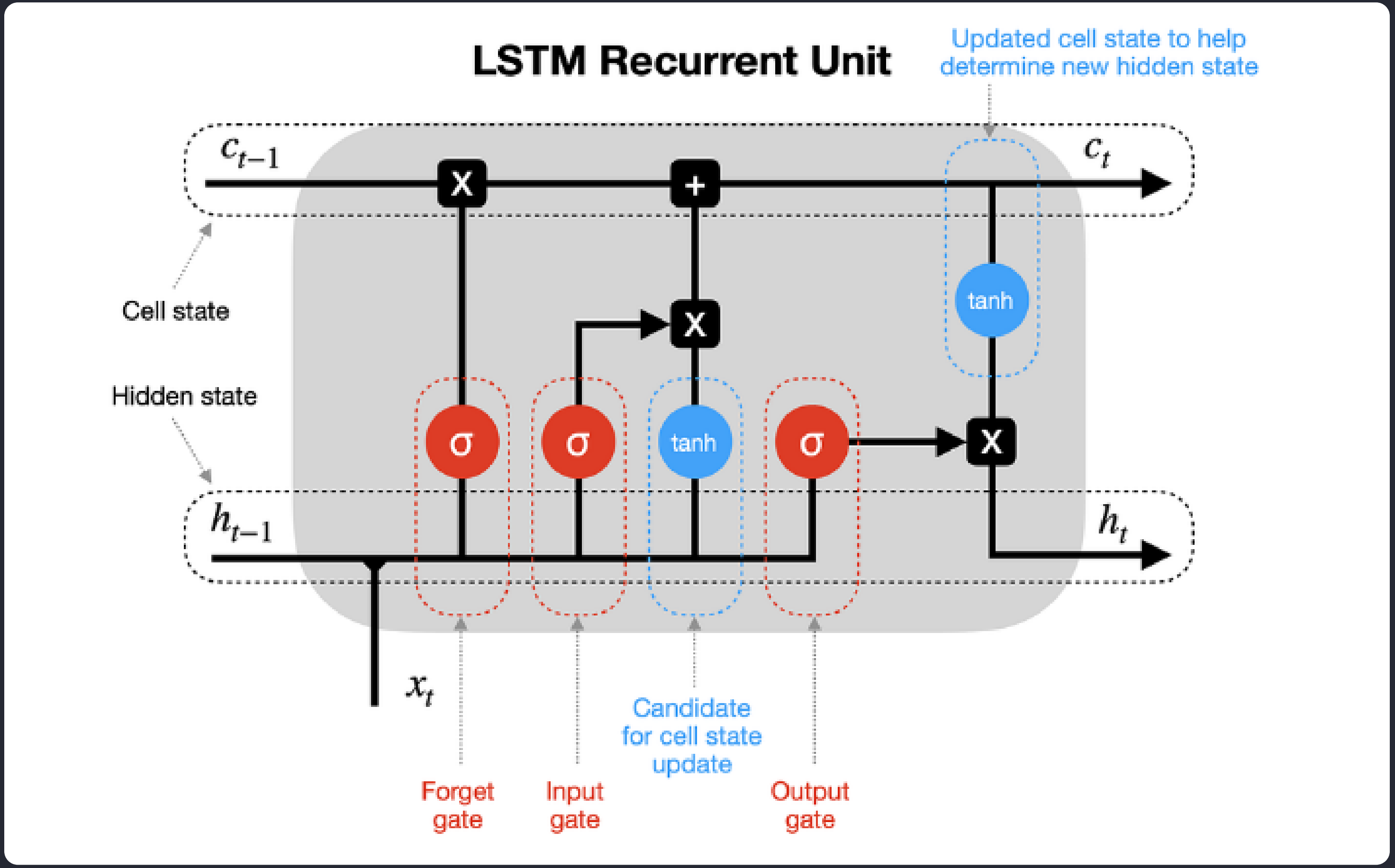
Support Vector Machine SVM

Support Vector Machines (SVM) is a powerful machine learning algorithm. It classifies data by finding the optimal hyperplane, maximizing margin between classes for effective pattern recognition in various applications.



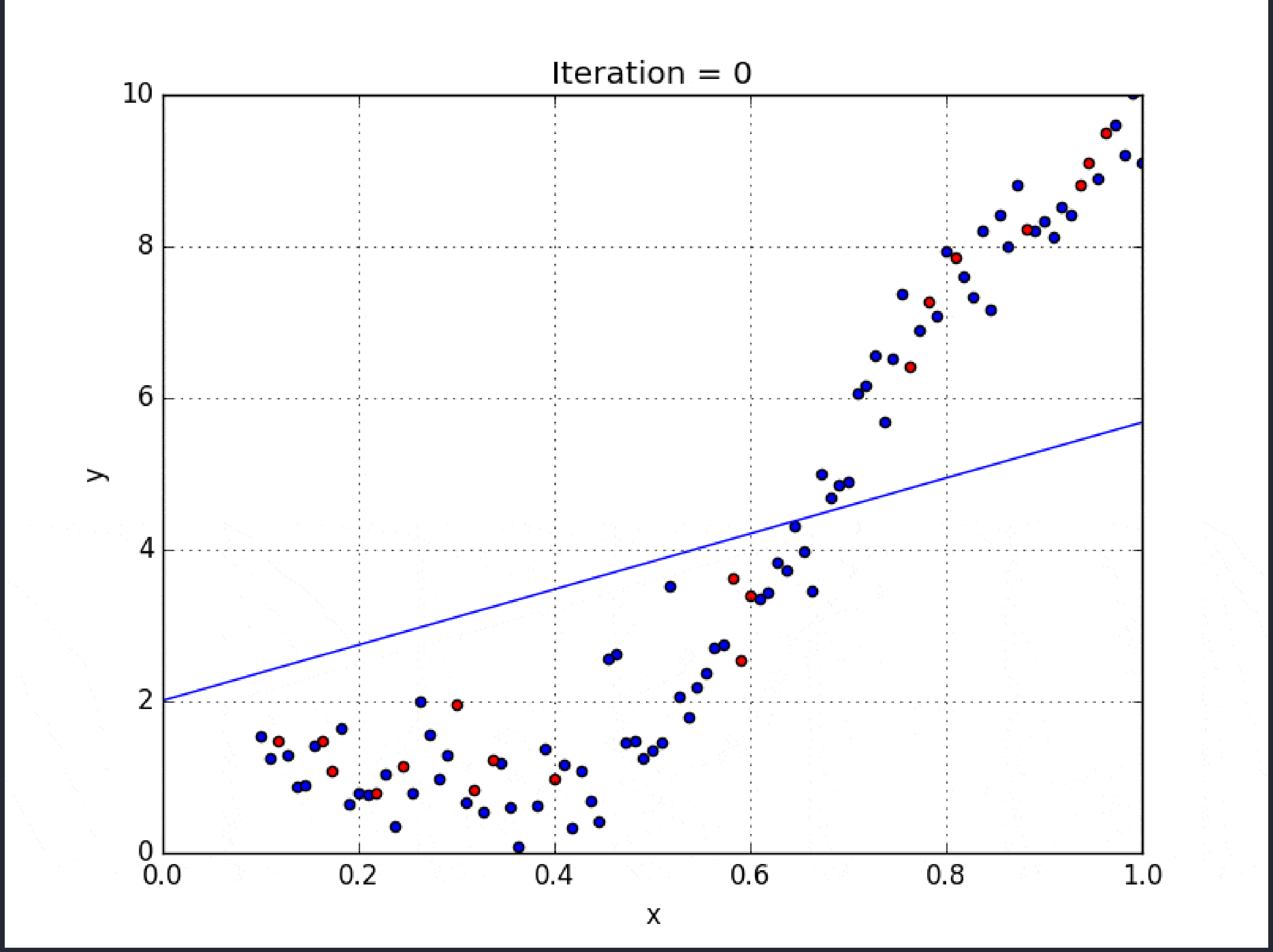
LTSM Neural Network

Long Short-Term Memory (LSTM) neural network is a specialized type of recurrent neural network (RNN) designed for capturing and retaining sequential patterns in data, overcoming the vanishing gradient problem.



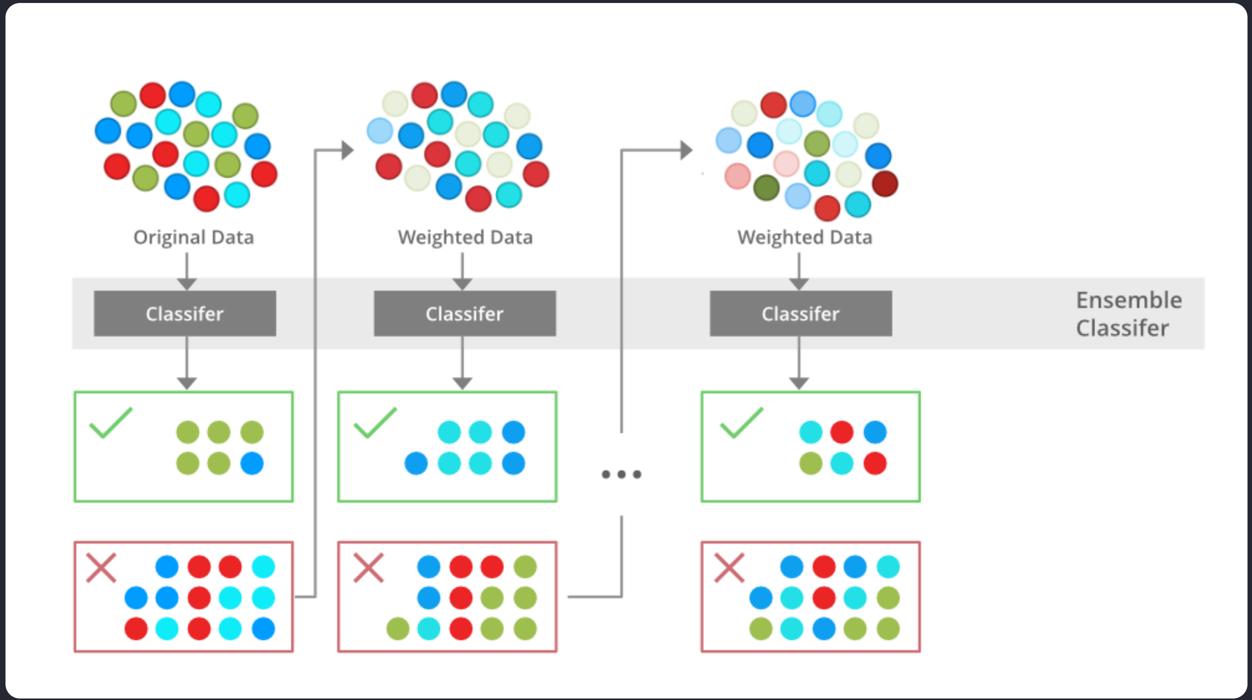
Lineer Regression

Linear regression in data mining models the relationship between a dependent variable and one or more independent variables using a linear equation. It aims to minimize the difference between observed and predicted values.



XGBoost

XGBoost, short for eXtreme Gradient Boosting, is a powerful machine learning algorithm known for its efficiency and accuracy. It's an ensemble learning method that combines the predictions of multiple weak models to create a robust and precise model. XGBoost is widely used in various domains, including finance, healthcare and optimization.



Inflexible-Semi-Flexible-Flexible Appliances

Inflexible Appliances:

- Furnace 1 and Furnace 2 [kW]: Heating systems typically need to operate at high performance during peak consumption times.
- Well [kW]: This typically provides essential water supply and might have limited flexibility in operation.

Semi-Flexible Appliances:

- Dishwasher [kW]: It could have some flexibility in its operating time for washing cycles and might work in an economical mode.
- Microwave [kW], Fridge [kW], Garage door [kW], and Wine Cellar [kW]: These are usually constant energy-consuming devices, yet their operating times might have some flexibility.

Flexible Appliances:

- Home office [kW]: Working hours here might be relatively flexible, especially for office functions.
- Kitchen 12 [kW], Kitchen 14 [kW], Kitchen 38 [kW], Living room [kW]: The operating times of these applian ces tend to be more flexible and can be programmed according to usage patterns and needs.

Final Calculation Cost of Energy Consumption

```
result_last=calculateCost(y_test)
savings_percentage = ((result_first - result_last) / result_first) * 100
print(f"The homeowners have achieved savings of {savings_percentage:.2f}% through this approach.")
```

OUT:

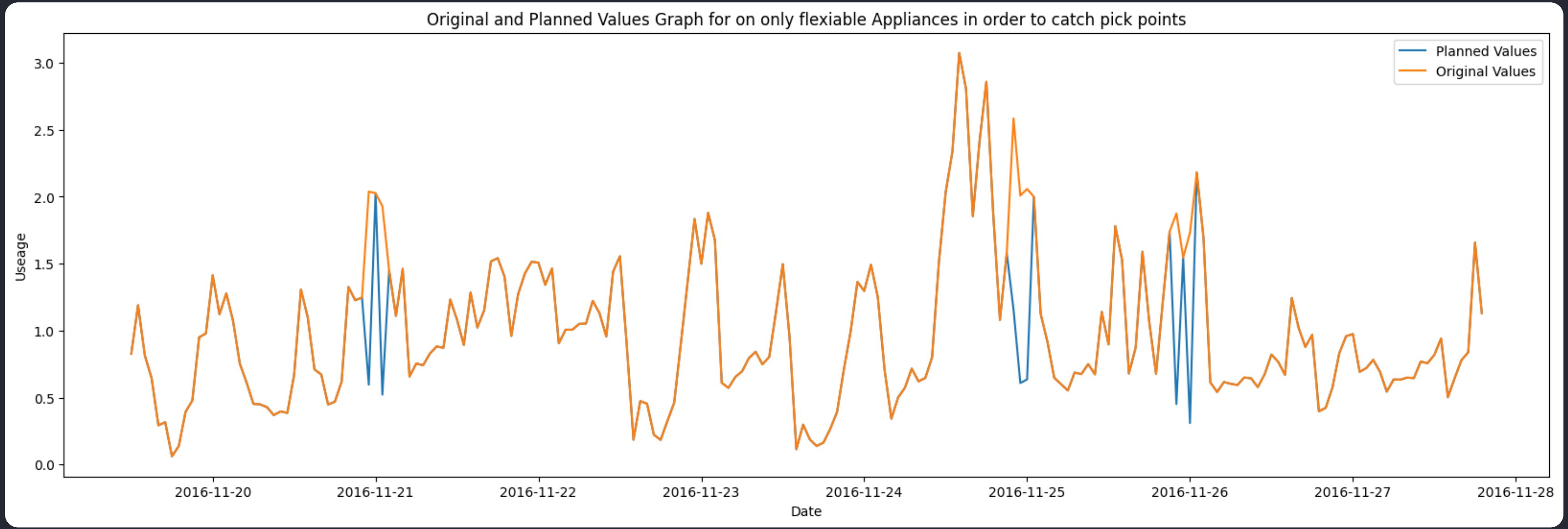
The homeowners have achieved appriximately savings of **17%** through this approach.

Our Main Contributions

- We achieved an improvement of approximately 17 percent in addressing homeowners' high electricity bill problem.
- For this specific issue, we evaluated the performance of 5 different models with 2 different datasets and 4 different error metrics.
- We defined categories named flexible, semi-flexible, and non-flexible, and explained how these can be utilized for optimization problems.

Experimental Results & Disscussions

FLEXIBLE APPLIANCES IN ORDER TO CATCH PICK POINTS



According to this graph, the program can catch peak points for flexiable appliances. Carrying them to another interval causes decrease usage of the smart home. We can see them on this graph very clearly. Also, I can be say that our model is also unsucessful to catch some peak points.

RESULT TABLE of DATASET 1

	Traning MAE	Training RMSLE	Training R^2	Training MSE	Validation MAE	Validation RMSLE	Validation R^2	Validation MSE
LSTM Dataset:1	0.255349	0.178668	0.581665	0.318016	0.260827	0.202471	0.352037	0.431021
Random Regressor Dataset:1	0.075932	0.054803	0.968934	0.023616	0.188398	0.150732	0.792158	0.138256
SVM Dataset:1	0.143073	0.109821	0.775772	0.170457	0.498815	0.317232	0.055289	0.628416
LSTM New Dataset:1	0.233005	0.155359	0.682868	0.241082	0.488547	0.312208	0.060505	0.625323

Test MAE	Test RMSLE	Test R^2	Test MSE
0.188530	0.147815	0.521445	0.110112
0.411855	0.255591	-0.746864	0.401939
0.141993	0.113013	0.683381	0.072851
0.278934	0.196683	0.103311	0.159362

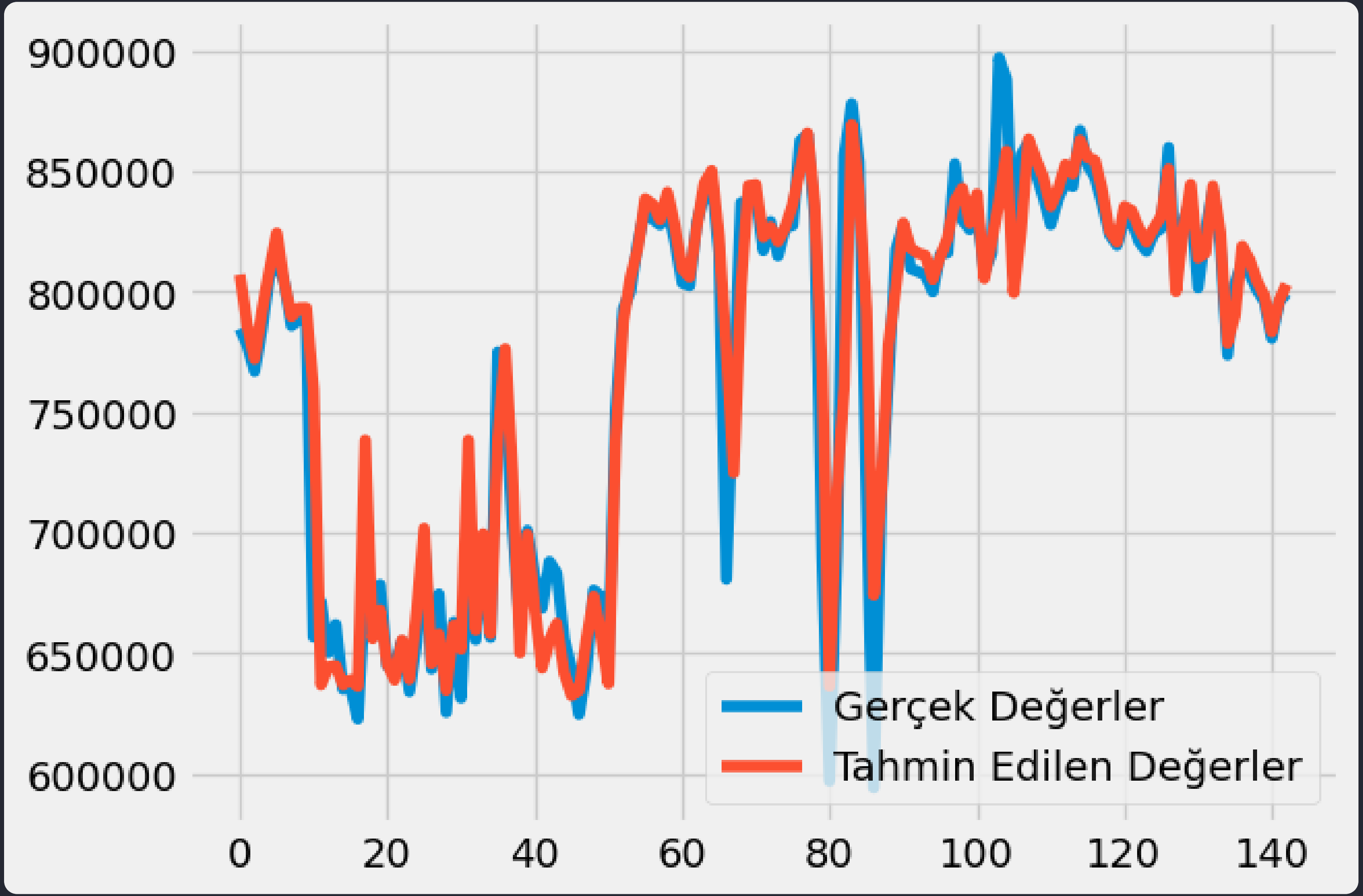
According to First Dataset

- Random Regressor is a good learner and has a good performance on validation and training sets. However, the test metrics of Random Regressor is very bad especially R^2 error. This means that Random Regressor produces its output in a random manner.
- SVM is also a good learner on training and test sets. However, SVM has a too bad performance on the validation set. This means that SVM has no general good guessing ability.
- Alternatively, we decided to use LSTM according to metrics.

RESULT TABLE OF DATASET 2

	Training MAE	Training MSE	Validation MAE	Validation MSE	Test MAE	Test MSE
LSTM	0.1890	0.0561	0.2624	0.0929	0.2917	0.1224
XGBoost	0.01536	0.00064	0.09641	0.01402	0.00580	0.04293
Linear	9.8121608 14482422 e-17	1.6445010 13600404 e-32	0.25178	0.06911	0.44421	0.21169

XGBoost Prediction Graph



Made with Gamma

According to Second Dataset

- LSTM and Linear models have more higher values than XGBooST in all types of datasets for MAE and MSE. Therefore, XGBoost is the best player for future predictions.

Advantages and & Disadvantages Our Method

- Our model is not an adaptive learner . This means that if there is a new appliance in the smart home, our model cannot control them and it may perform an undesired manner.
- Our model is a good model in terms of easy constructing. In research stage, we came acroos FLC and ANFIS systems . FLC performs in fuzzy rules and fuzzy dataset. Smart home system programmers may find constructing them quite intricate. When it comes to ANFIS, this system has a rather complex neural network structure and can cause a lot of time loss for novice programmers.

Conclusion

In this presentation, we explored the topic of energy efficiency optimization for smart homes. We discussed the increasing energy consumption due to the rise of smart home devices and the need to find solutions to either produce more energy or consume less energy. We proposed the use of data mining techniques such as Random Forest Regressor,Lineer Regression,XGBoost, Support Vector Machine SVM, and LTSM Neural Network.

Through our experiments, we observed that our program was able to effectively capture peak points for flexible appliances, leading to decreased energy usage. However, it was not entirely successful in capturing all peak points. We also evaluated our method based on two datasets and analyzed the advantages and disadvantages. Overall, our approach showed promising results in enhancing energy efficiency in smart homes.

In conclusion, our research contributes to the ongoing efforts in optimizing energy consumption in smart homes. By leveraging data mining techniques and considering the flexibility of appliances, we can make significant progress in reducing energy waste and creating more sustainable living environments.

Thanks For Your Listening

GROUP NO :

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