



MODELLING RESIDENTIAL END-USE ELECTRICITY CONSUMPTION USING STATISTICAL AND ARTIFICIAL INTELLIGENCE APPROACHES AND DETERMINING THE EFFECTIVE SAVING MEASURES

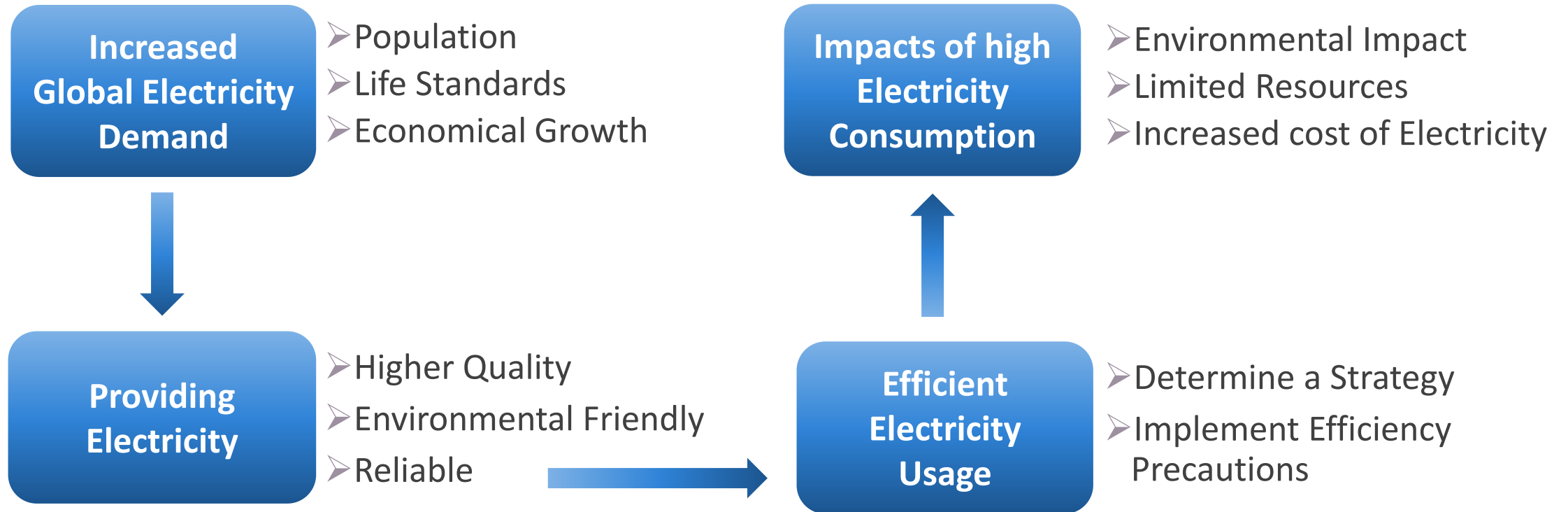
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Global Electricity Use



End-Use Electricity Efficiency Studies in Residential Sector

End-use electricity consumption estimation methods;

- Engineering Models
- Statistical Models
- Artificial Intelligence Models

Purpose of the Study

- Developing both «*Statistical*» and «Artificial Intelligence» based models to identify the electricity consumption of major end-uses
- Comparing the prediction performances of the models
- Implementing the efficient saving measures for electricity consumption

Previous Studies on CDA & ANFIS Approach

Parti and Parti (1980);

- CDA was first performed by Parti and Parti
- They were focused on the determination of electricity demand functions with respect to the particular appetences by using a covariance framework analysis
- Engineering method results were compared with CDA approach

Jang (1993);

- ANFIS was first introduced to the literature by Jang in 1993
- Takagi-Sugeno method was used as hybrid learning procedure

Previous Studies on CDA & ANFIS Approach

CDA approach has been applied by researchers to estimate;

- *Electricity consumption by using load curves as metered data*
- *End-use gas demand prediction with respect to the electricity consumption*
- *Appliance based energy consumption for Demand Site Management (DSM) planning studies*
- *The effects of appliance usage patterns based on the socio-economic properties*
- *CDA results are compared with econometric methods, engineering methods, etc...*

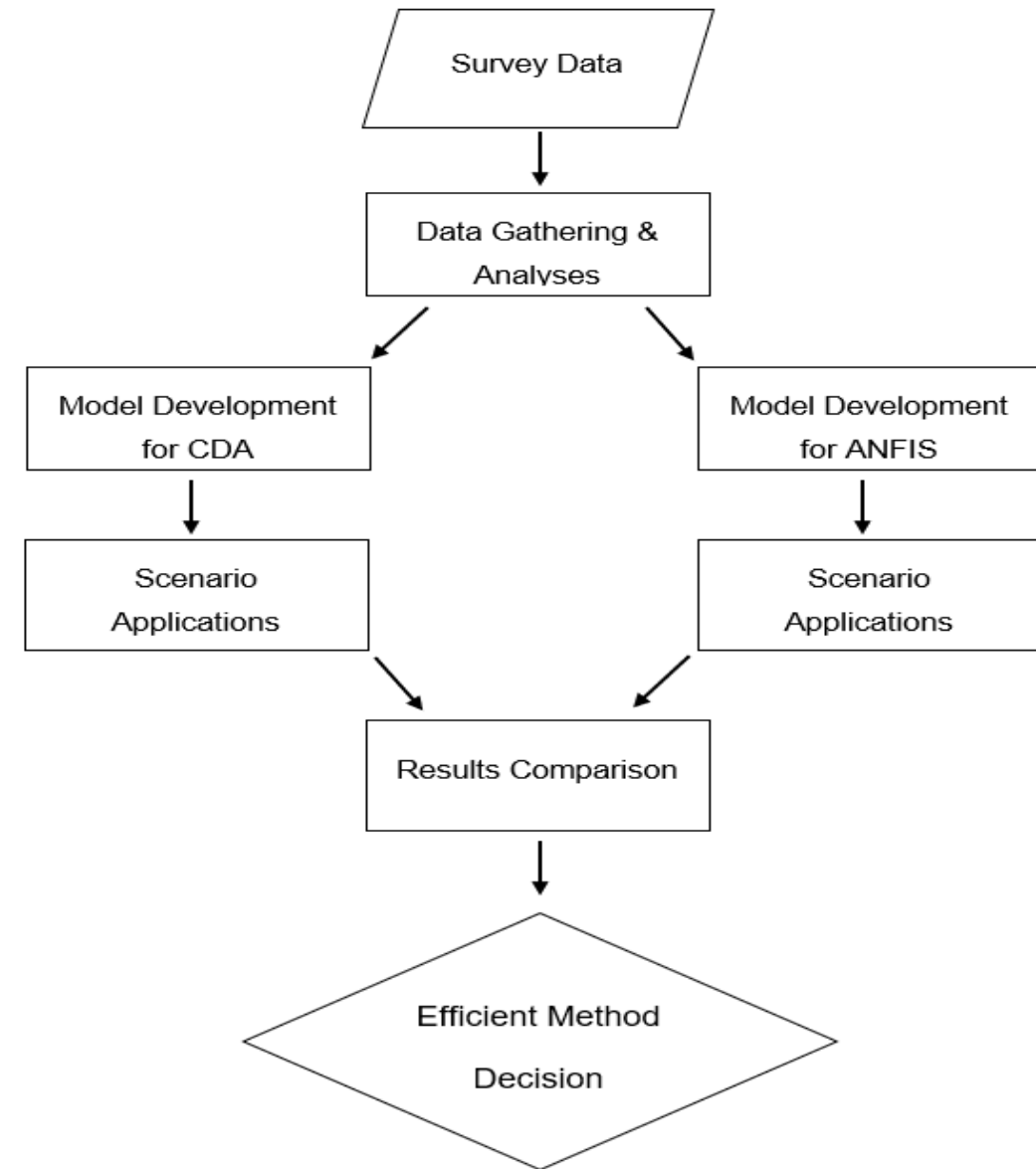
Previous Studies on CDA & ANFIS Approach

ANFIS approach has been applied by researchers to estimate;

- *Dailiy air pollution level*
- *Wind forecasting model efficiency for power generation*
- *Electricity consumption by observing the accuracy of applying different simulations and methods*
- *Travel time on a river with respect to the flow velocity*
- *Electric energy load and energy consumption*
- *ANFIS results are compared with different types of artificial neural network based methods*

Data Sources & Methodology

- Database of a detailed survey is used for the development of the models
- The survey was conducted to 260 homes in Ankara in 2012
- This survey contains 45 questions
- Detailed characteristic and usage patterns on 92 different types of appliances were recorded
- Billing data of the surveyed homes were also collected



Development of CDA Model

Basic formulization of CDA approach \rightarrow $HEC_{it} = \sum_{j=1}^J (UEC_{ij,t} * S_{ij})$


HEC_{it} : electricity consumption by household i in period t , kWh

$UEC_{ij,t}$: end-use j unit electricity consumption of household i in period t , kWh

S_{ij} : household i 's binary indicator ownership as per ownership of appliance j

Development of CDA Model

87% of electricity consumption in overall usage



Percent share of each appliance is calculated and major appliances which are considered in the model are determined

Appliance	Ownership	Saturation, %	Avg EC, kWh	Avg EC*Sat, kWh	Share, %
Main Refrigerator	260	100%	683	683	25.8%
Lighting	260	100%	250	250	9.4%
Dishwasher	221	85%	234	199	7.5%
Iron	257	99%	191	189	7.1%
Main Television	255	98%	171	168	6.3%
Vacuum Cleaner	259	100%	160	160	6.0%
Washing Machine	257	99%	131	129	4.9%
Oven	230	88%	129	114	4.3%
Boiler	166	64%	139	89	3.3%
Desktop Computer	98	38%	195	73	2.8%
Secondary Television	152	58%	101	59	2.2%
Receiver	196	75%	75	57	2.1%
Notebook	148	57%	81	46	1.7%
Deep Freezer	35	13%	340	46	1.7%
Secondary Refrigerator	17	7%	605	40	1.5%
Kettle	133	51%	70	36	1.4%
Dryer	8	3%	1015	31	1.2%
Kitchen Fan	148	57%	50	29	1.1%
Electric Stove (Auxiliary)	28	11%	228	25	0.9%
Tea Maker	66	25%	92	23	0.9%

Development of CDA Model

R	0.878
R Square	0.771
Adjusted R Square	0.759
Std. Error of the Estimate	419.36
Durbin-Watson	1.778

$$\begin{aligned}
 \text{HEC} = & 662.500 + [91.334*(\text{DW}*\text{CYC}_{\text{DW}})] + \\
 & [208.803*(\text{IR}*\text{HUSE}_{\text{IR}})] + \\
 & [91.100*(\text{VC}*\text{HUSE}_{\text{VC}})] + \\
 & [108.797*(\text{WM}*\text{CYC}_{\text{WM}})] + \\
 & [167.038*(\text{OV}*\text{HUSE}_{\text{OV}})] + \\
 & [2.056*(\text{BOIL}*\text{AREA})] + \\
 & [18.729*(\text{PC}*\text{PC}*\text{HUSE}_{\text{PC}})] + \\
 & [2.917*(\text{TV2}*\text{SCR}_{\text{TV2}})] + \\
 & [31.729*(\text{REC}*\text{HUSE}_{\text{REC}})] + \\
 & [2.236*(\text{REF2}*\text{VOL}_{\text{REF2}})] + \\
 & [0.283*(\text{LGHT}*\text{W-INCA}_{\text{LGHT}})] + \\
 & [0.608*(\text{LGHT}*\text{W-CFL}_{\text{LGHT}})]
 \end{aligned}$$

Development of ANFIS Model

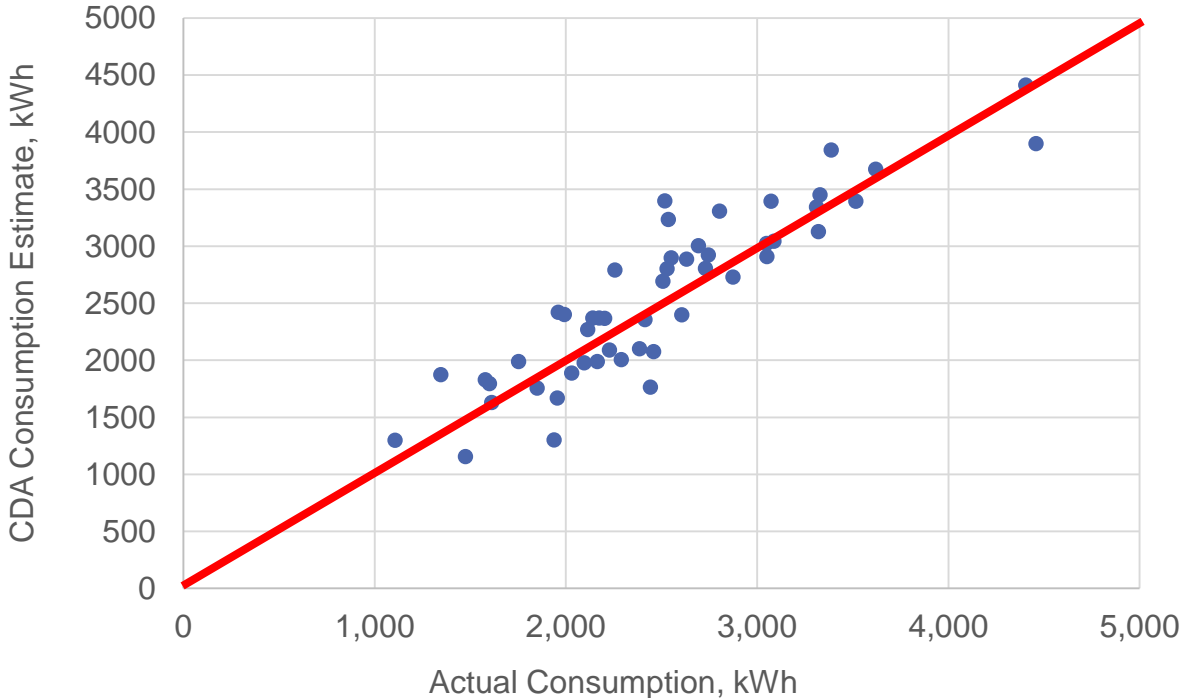
- NN is an algorithm that realizes the ability of learning and creating new information without any help.
- This algorithm is inspired by biological nervous systems.
- Basically, the aim of NN is to provide the computers with the ability of biological neural systems to solve complex events.
- Fuzzy Logic is basically «the concept of uncertainty» that creates rule based system similar to brain knowledge processing system.
- This is done by creating if-then rules with appropriate membership functions
- ANFIS combines NN learning structure with fuzzy logic membership functions

Development of ANFIS Model

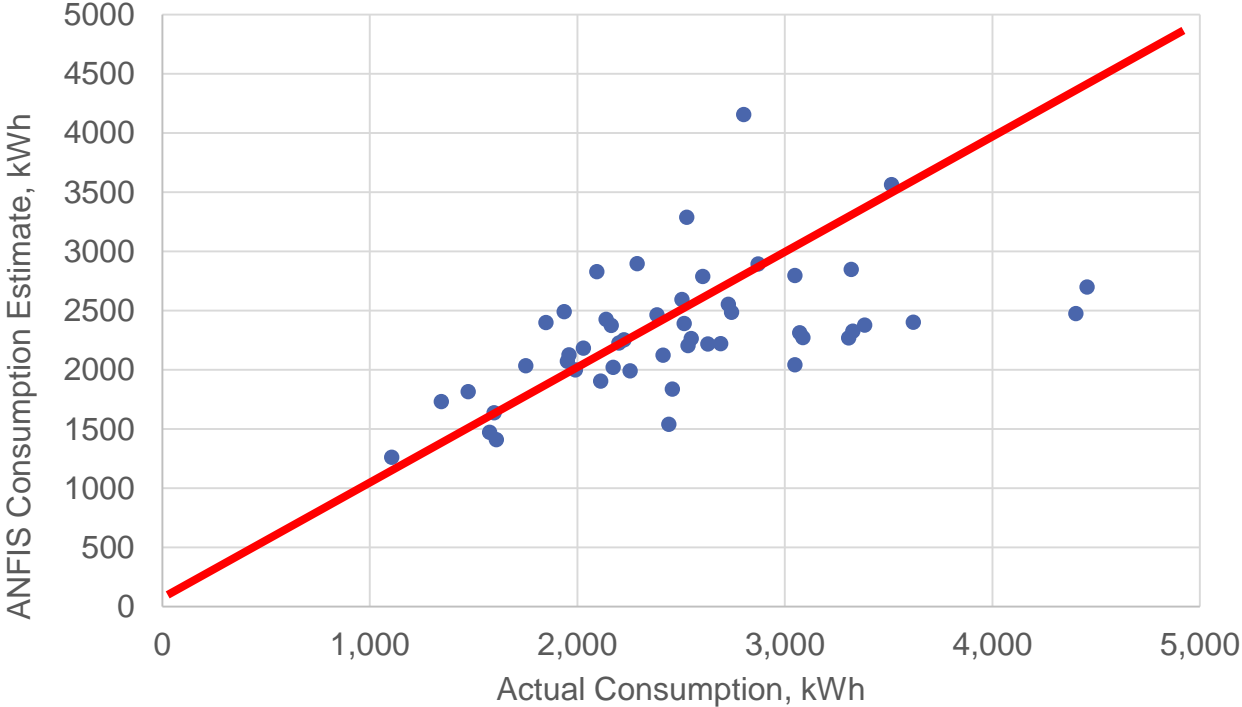
```
Input_Data = ANFISModel1(1:200,1:24);
Output_Data = ANFISModel1(1:200,25);
Train_Data = ANFISModel1(1:200,:);
Test_Data = ANFISModel1(201:250,:);
RangesOfInfluence= 0.5;
fismat =genfis2(Input_Data,Output_Data,RangesOfInfluence);
epoch_n      = 5;
error_tolerance_rate = 0.005;
trnOpt = [epoch_n, error_tolerance_rate];
dispOpt = ones (1,4);
[out_fis, trnErr] = anfis(Train_Data, fismat, trnOpt, dispOpt);
MAPE = trnErr(length(trnErr));
anfis_result= evalfis(Test_Data(:,1:24), out_fis);
comp = [Test_Data(:,25), anfis_result, Test_Data(:,25) anfis_result];
```

TRIAL	Number of Input Variables	MAPE of the Model Output	MAPE of the Test Data
Model-1	12	0.5109	76%
Model-2	12	0.0535	39%
Model-3	12	0.0763	34%
Model-4	14	0.0568	31%
Model-5	17	0.4393	23%
Model-6	20	0.2802	20%
Model-7	24	0.2521	17%

Results and Discussions



MAPE of CDA : 12.1%



MAPE of ANFIS : 17%

Scenario 1 → Lighting

- Households using incandacent lamps at housholds are replaced with compact fluorescent lamps.
- Applied for 195 households

Description	Lighting EC	Total EC
Original consumption, kWh	176	2,549
Consumption after scenario application, kWh	159	2,532
Percent reduction, %	9.5	2.05

Scenario 2 → Dishwasher

- All households with weekly dishwasher loads of 3 or more are reduced to 3.
- Applied for 197 households

Description	Dishwasher EC	Total EC
Original consumption, kWh	360	2,752
Consumption after scenario application, kWh	242	2,654
Percent reduction, %	32.7	4.3

Scenario 3 → Washing Machine

- All households with weekly washing machine loads of 2 or more are reduced to 2.
- Applied for 230 households

Description	Washing Machine EC	Total EC
Original consumption, kWh	224	2,633
Consumption after scenario application, kWh	186	2,595
Percent reduction, %	16.9	1.4

Conclusion

- CDA model results in a higher prediction performance than ANFIS model.
 - CDA → MAPE of 12.1%
 - ANFIS → MAPE of 17%
- ANFIS has a powerful learning structure but requires a larger dataset to work efficiently
- Possible reductions in total electricity consumption achieved with;
 - Replacing incandescent lamps → 2%
 - Reducing dishwasher loads → 4%
 - Reducing washing machine loads → 1%

Thank You