TECHNISCHE UNIVERSITÄT CHEMNITZ

Master Thesis

Easy Smart Grid GmbH

A smart scheduling algorithm for a decentralized energy management system

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Chair of Communication Networks

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TU Chemnitz ,
Chair of Communication Networks

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Motivation

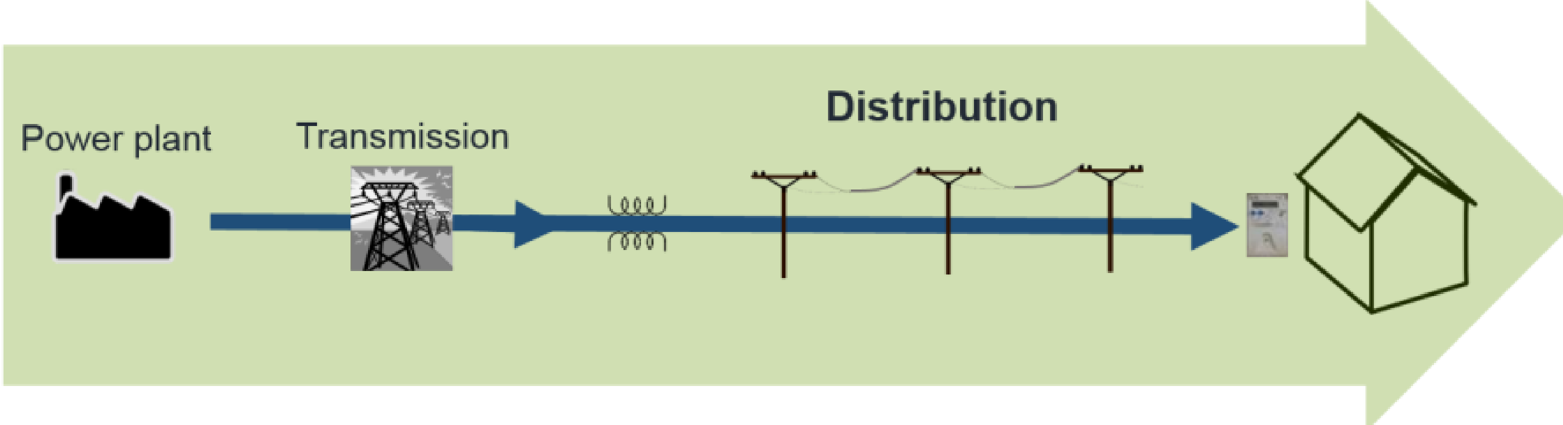
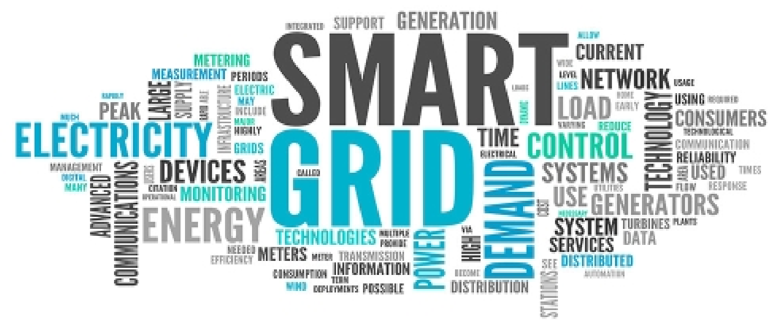


***Fig 1**.Traditional Electrical Grid [1]*

Current problems

- Infrastructure problems
  - Black outs
  - Brown outs
  - High cost
- Inflexibility
- Lack of information transparency



Upcoming challenges : Scarcity of resources, Distributed power supply Automated control through out the grid

SMART GRID

Supporting technologies

- Real time pricing
- Advance meter reading : AMI or Automated meter reading : AMR
- Enable Home area network : HAN

Characteristics of HAN

- Motivates the customers
  - Modified COEC
  - Real time demand-pricing information
  - Low installation cost
  - Reduced system peak
  - Efficient and smart appliances
- Resist Attack
- Accommodate all the generation and storage options
- Optimize the assets and operates efficiently
- Smart in-home system

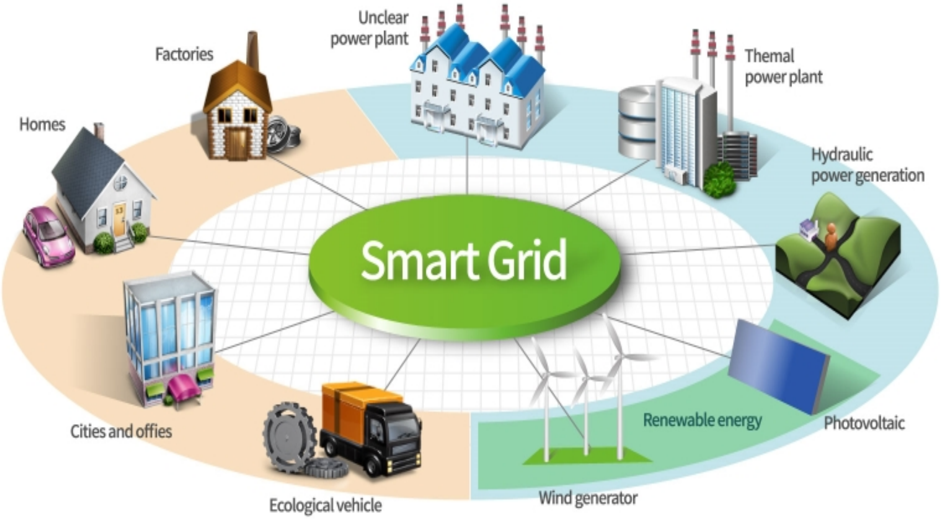


Fig 2*. Smart Grid [2]*

Supporting technologies

- Real time pricing
- Advance meter reading : AMI or Automated meter reading : AMR
- Enable Home area network : HAN

Characteristics of HAN

- Motivates the customers
    - Modified COEC
    - Real time demand-pricing information
    - Low installation cost
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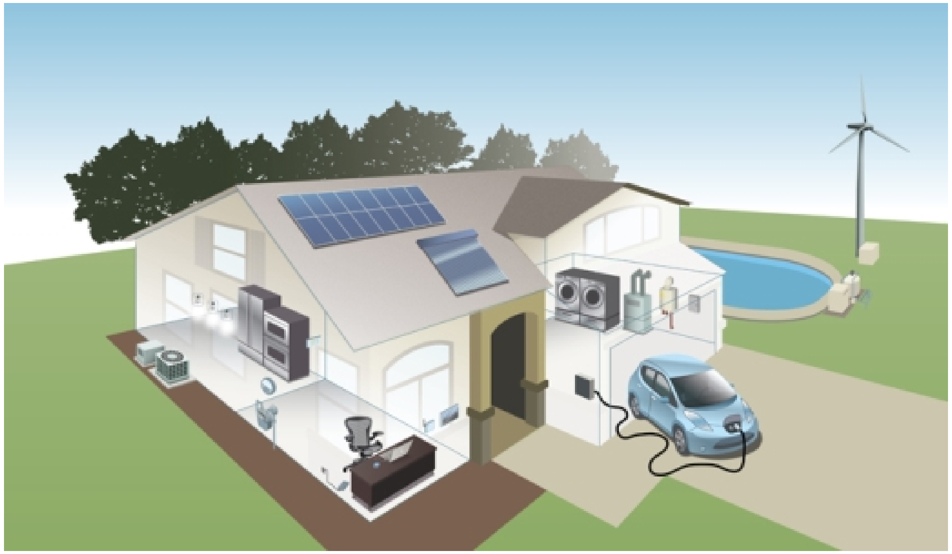

Fig 2. *HAN [3]*

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Outline of algorithm

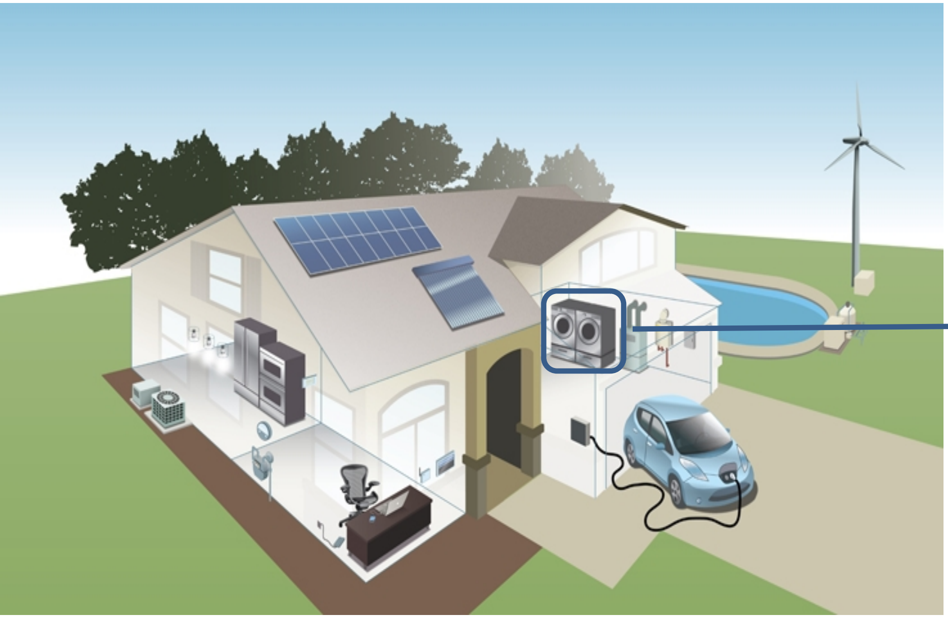


Fig 3. HAN [3]

3 Phases of algorithm

Prediction Phase / Phase 1

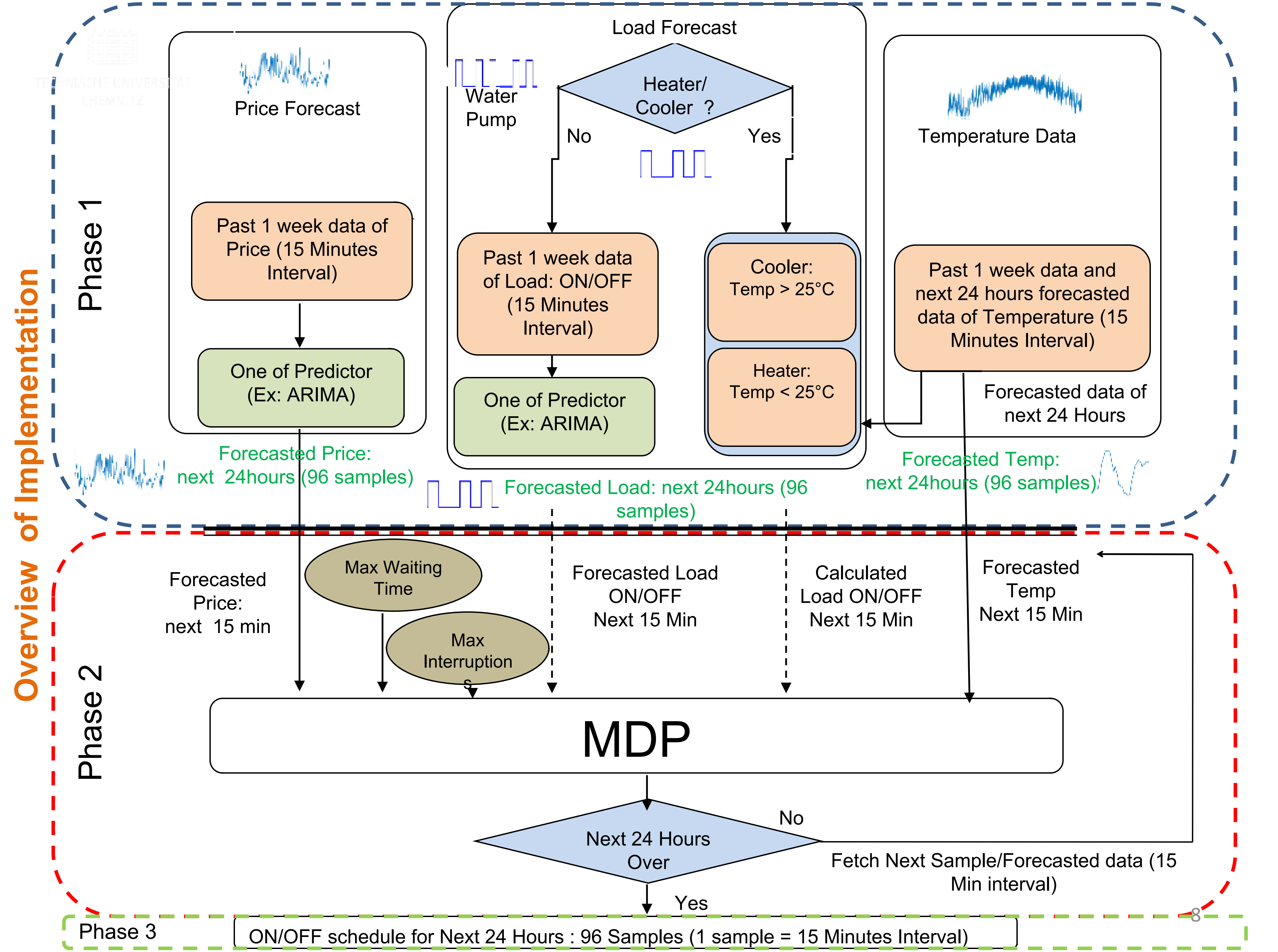
Predict next 24h device switching pattern and electricity price information .

Optimization Phase / Phase 2

The objective of this phase is to optimize the forecasted switching patterns (ON-OFF patterns)

Phase 3

Once the device switching schedule is optimized in phase 2, the controller hardware takes over, to control the device state of operation


Overview of Implementation
Phase 1
Price Forecast
Past 1 week data of Price (15 Minutes Interval)
One of Predictor (Ex: ARIMA)
Load Forecast
Water Pump
Heater/ Cooler ?
No
Yes
Past 1 week data of Load: ON/OFF (15 Minutes Interval)
One of Predictor (Ex: ARIMA)
Cooler: Temp > 25°C
Heater: Temp < 25°C
Temperature Data
Past 1 week data and next 24 hours forecasted data of Temperature (15 Minutes Interval)
Forecasted data of next 24 Hours
Forecasted Price: next 24hours (96 samples)
Forecasted Load: next 24hours (96 samples)
Forecasted Temp: next 24hours (96 samples)
Phase 2
Forecasted Price: next 15 min
Max Waiting Time
Max Interruptions
Forecasted Load ON/OFF Next 15 Min
Calculated Load ON/OFF Next 15 Min
Forecasted Temp Next 15 Min
MDP
Next 24 Hours Over
No
Fetch Next Sample/Forecasted data (15 Min interval)
Yes
Phase 3
ON/OFF schedule for Next 24 Hours : 96 Samples (1 sample = 15 Minutes Interval)

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Prediction phase

Price Prediction →

Predictor models
Neural Network
Linear regression
Non-Linear regression
ANFIS
ARIMA

Independent variables
Minutes Of Day
Previous week Same Time Price
Average Previous Week Same Day Price
Temperature, Relative humidity, Dew point, Wind speed

Load prediction →

Predictor models
Neural Network
Linear regression
Non-Linear regression
ANFIS
ARIMA

Independent variables
Minutes Of Day
Weekend is true
Weeks Day Number
Hour Of Day
Previous week Same Time Load
Average Previous Week Same Day Load
Temperature, Relative humidity, Dew point, Wind speed

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Prediction phase

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Prediction phase

Price Prediction ⇒

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Load prediction →

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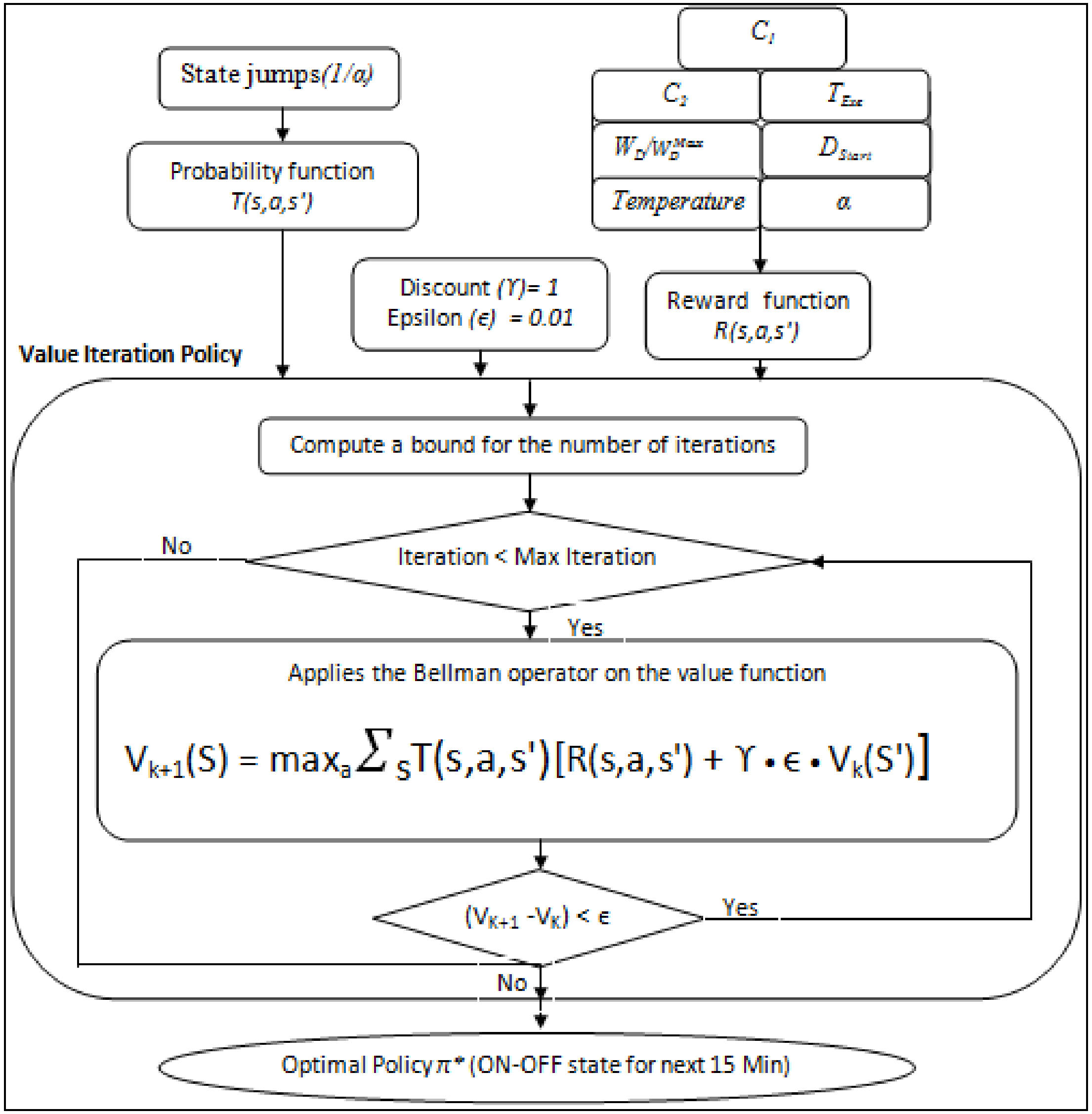
Markov Decision Process(MDP)

Forecasted LOAD and PRICE is applied as input to MDP (Formulated as MDP problem). MDP outputs/determines, ON/OFF state of the device for next 15 Minutes.

MDP runs for every 15 Minutes.MDP determines ON/OFF state(of next 15 Minutes) based on 6 parameters and additional Temperature(If Temp Dependent Device).

- Price for next 1 hour *(C_1)*
- Electricity price at a specific instant of time *t (C_2)*
- Total device execution time left *(T_{Exe})*
- Present waited time *(W_D/ W_{DMax})*
- Alpha: state jumps *(α)*
- Checks, if device needs to be turned ON that day *(D_{Start})*

Key Plots : Optimization / Phase 2 implementation



MDP : Formation of Transition Probability

The transition probability is a 5 x 5 x 2 matrix, i.e. 5 states [S1, S2, S3, S4, S5] and 2 actions [ON, OFF].

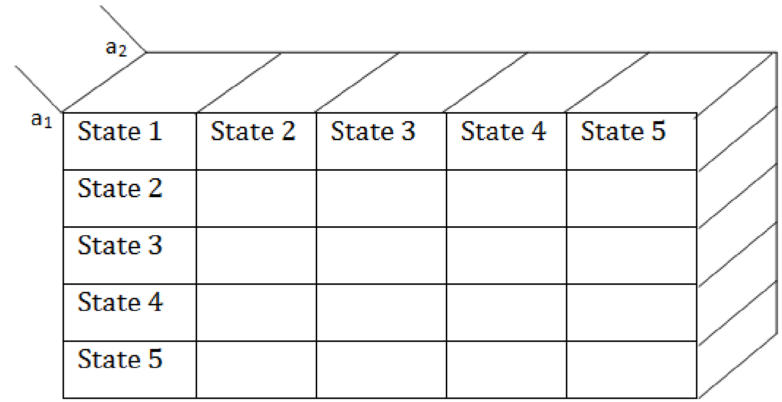
$$C_t^{total\_day} = \mathrm{RTP} * \mathrm{Load} = \zeta_t * \omega_{Load}$$

↓

$$Step_{size} = Max\ (\ C_t^{total\_day})\ /\ 5$$

↓

$$\mathrm{T(s,a,s')} = \frac{Number\ of\ transisions\ from\ state\ S\ to\ S'}{Total\ number\ of\ transistions\ from\ the\ state\ S}$$



Transition probability is a 5 x 5 x 2 matrix

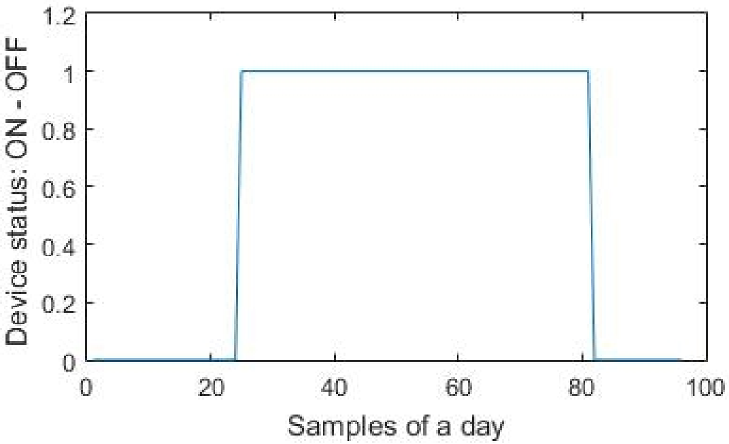
```
val(:,:,2) =

    0.9737         0         0         0    0.0263
    0.2000    0.6000    0.2000         0         0
         0    0.1429    0.7143    0.1429         0
         0         0    0.1250    0.7500    0.1250
         0    0.0270         0    0.0270    0.9459
```

Transition probability for ON

MDP : Formation of Transition Probability

The transition probability is a 5 x 5 x 2 matrix, i.e. 5 states [S1, S2, S3, S4, S5] and 2 actions [ON, OFF].



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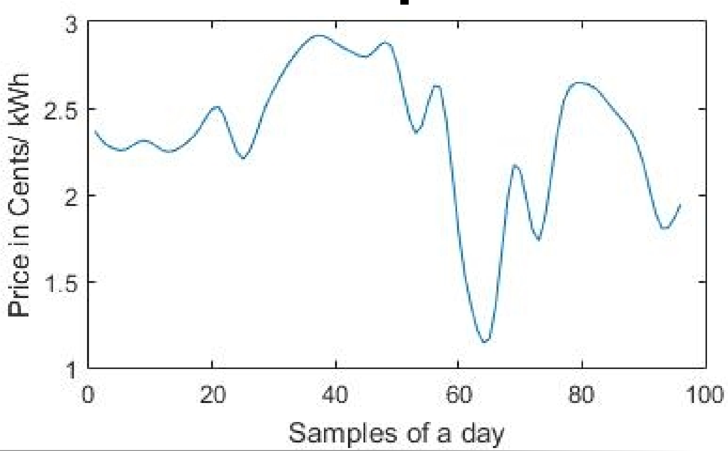
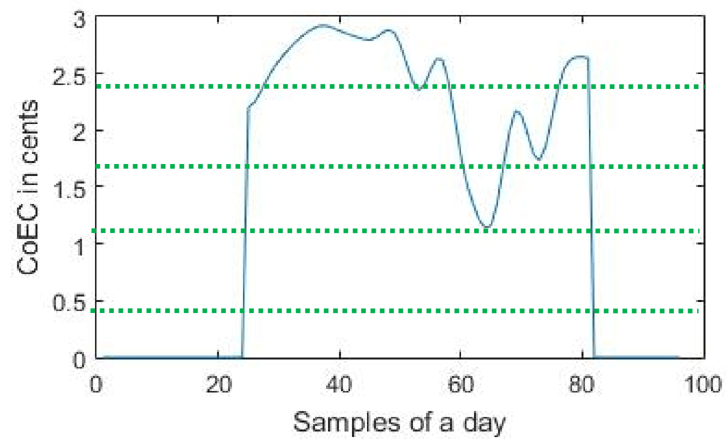


$$C_t^{total\_day} = \mathrm{RTP} * \mathrm{Load} = \zeta_t * \omega_{Load}$$

$$Step_{size} = Max\ (\ C_t^{total\_day}\ )\ /\ 5$$



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MDP : Formation of Transition Probability

The transition probability is a 5 x 5 x 2 matrix, i.e. 5 states [S1, S2, S3, S4, S5] and 2 actions [ON, OFF].

$$C_t^{total\_day} = \mathrm{RTP} * \mathrm{Load} = \zeta_t * \omega_{Load}$$

$$\downarrow$$

$$Step_{size} = Max\ (\ C_t^{total\_day}\ )\ /\ 5$$

$$\downarrow$$

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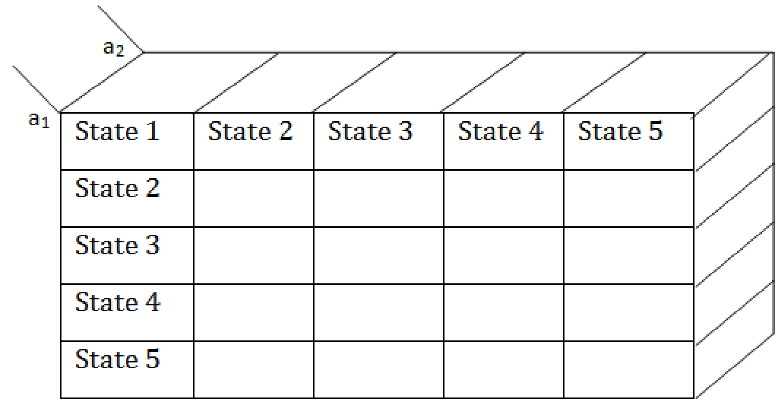

Transition probability is a 5 x 5 x 2 matrix

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val(:,:,2) =


    0.9737         0         0         0    0.0263
    0.2000    0.6000    0.2000         0         0
         0    0.1429    0.7143    0.1429         0
         0         0    0.1250    0.7500    0.1250
         0    0.0270         0    0.0270    0.9459
```

Transition probability for ON

MDP : Formation of Reward function

$$R = \alpha * C_1 * C_2 * T_{Exe} * \frac{W_D}{W_D^{Max}} * D_{Start} * Temperature$$

Where,

α	*: State jump factor.*
C_1	*: Cost for next 1 hour.*
C_2	*: How Low is the present cost*
T_{exe}	*: Device execution time left.*
W_D/W_{DMax}	*: Present waited time.*
D_{start}	*: Checks, if device needs to be turned ON that day.*
Temperature	*: Temperature (If Temp Dependent Device).*

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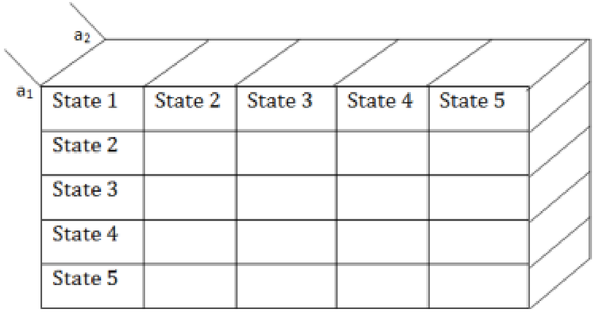
W_D/W_{DMax}	*: Present waited time.*
D_{start}	*: Checks, if device needs to be turned ON that day.*
Temperature	*: Temperature (If Temp Dependent Device).*

Jump from a higher CoEC state to a lower CoEC is assigned better reward than a jump from lower to higher. Where state *S* is the initial state and *S*' is the next state. The index value ranges from 1 to 5.

$$\alpha = \frac{Index\ of\ S}{Index\ of\ S'}$$



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Temperature	: Temperature (If Temp Dependent Device).

$$H_{std(X)} = \mu + std(X)$$

$$C_1 = \Sigma_4 \{True([\omega_{Price}^{t=0}, \omega_{Price}^{t+15}, \omega_{Price}^{t+30}, \omega_{Price}^{t+45}] < H_{std(X)}\}$$

Where,

μ: *Mean of the Forecasted price data: set of 96 samples, each sample at15 min interval.*

$std(X)$: *Standard Deviation of the Forecasted price data: set of 96 samples, each sample at 15 min interval.*

MDP : Formation of Reward function

$$R = \alpha * C_1 * C_2 * T_{Exe} * \frac{W_D}{W_D^{Max}} * D_{Start} * Temperature$$

Where,

α	: State jump factor.
C_1	: Cost for next 1 hour.
C_2	: How Low is the present cost
T_{exe}	: Device execution time left.
W_D/W_{DMax}	: Present waited time.
D_{start}	: Checks, if device needs to be turned ON that day.
Temperature	: Temperature (If Temp Dependent Device).

$$C_2 = \frac{\omega_{Price}^t - P_{Min}}{P_{Max} - P_{Min}}$$

Where,

ω_{Price}^t : *Electricity price at the current sampling time.*

P_{Min} : *Minimum electricity price of the day: Min{set of prices:96samples} = min{*ω_{Price} *}*

P_{Max} : *Maximum electricity price of the day: Max{set of prices:96 samples}= max{*ω_{Price} *}*

MDP : Formation of Reward function

$$R = \alpha * C_1 * C_2 * T_{Exe} * \frac{W_D}{W_D^{Max}} * D_{Start} * Temperature$$

Where,

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C_1	: Cost for next 1 hour.
C_2	: How Low is the present cost
T_{exe}	: Device execution time left.
W_D/W_{DMax}	: Present waited time.
D_{start}	: Checks, if device needs to be turned ON that day.
Temperature	: Temperature (If Temp Dependent Device).

This reward component assigns lower reward during the devices initial execution time, thereby less curtailment on its operation. On the other hand, this reward component forces the device to remain turned ON, when the device approaches its required execution time, thereby allowing the device to execute till the completion of specific task

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Temperature	*: Temperature (If Temp Dependent Device).*

A reward component for waiting time of the device. The reward increases as the device's present waiting time approaches the device's maximum waiting time

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C_2	: How Low is the present cost
T_{exe}	: Device execution time left.
W_D/W_{DMax}	: Present waited time.
D_{start}	: Checks, if device needs to be turned ON that day.
Temperature	: Temperature (If Temp Dependent Device).

This reward component scales the reward function with '*1*' if at all the device is required to be scheduled/turned ON that particular day or else scales with '*0*'. As a consequence the scenario in which the devices being turned OFF at weekends are covered.

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MDP : Formation of Reward function

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C_2 : How Low is the present cost

T_{exe} : Device execution time left.

W_D/W_{DMax} : Present waited time.

D_{start} : Checks, if device needs to be turned ON that day.

Temperature : Temperature (If Temp Dependent Device).

$$Temperature = \frac{\omega^t_{Temperature} - Temperature_{Min}}{Temperature_{Max} - Temperature_{Min}}$$

Where,

$\omega^t_{Temperature}$: *Temperature at the current sampling time.*

$Temperature_{Min}$: *Minimum of entire day's temperature*

$Min\{set\ of\ temperature{:}96samples\} = min\{\omega_{Temperature}\}$

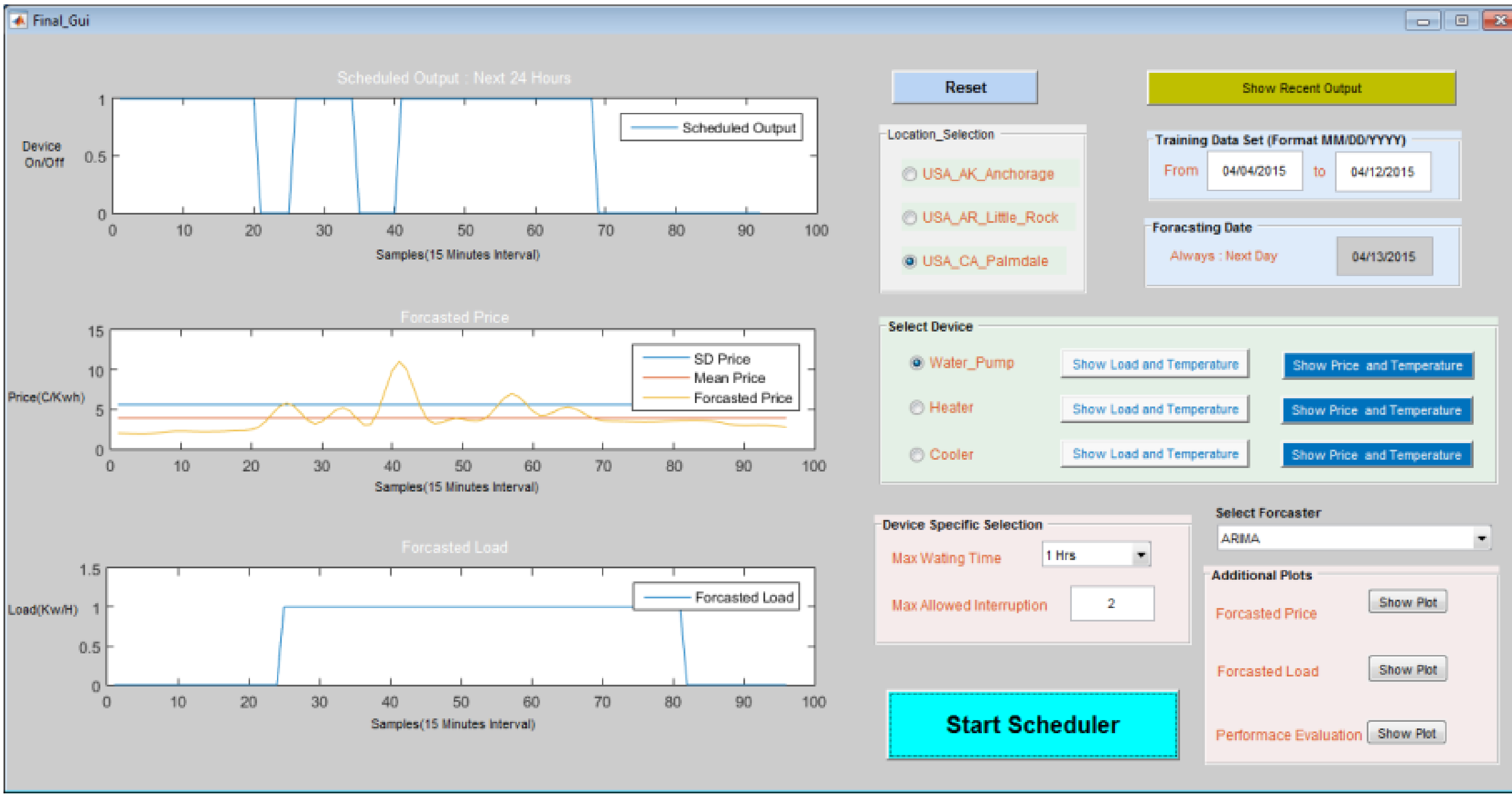
$Temperature_{Max}$: *Maximum of entire day's temperature*

$Max\{set\ of\ temperature{:}96samples\} = max\{\omega_{Temperature}\}$

MATLAB Graphical user interface(GUI)

Required Load scheduling is achieved. A simulator is designed for ease of use and assessment .

SMART LOAD SCHEDULER



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Functionality : Water Pump

Water Pump: Forecast Date(April 29th of 2015)

1) Cost for next 1 hour

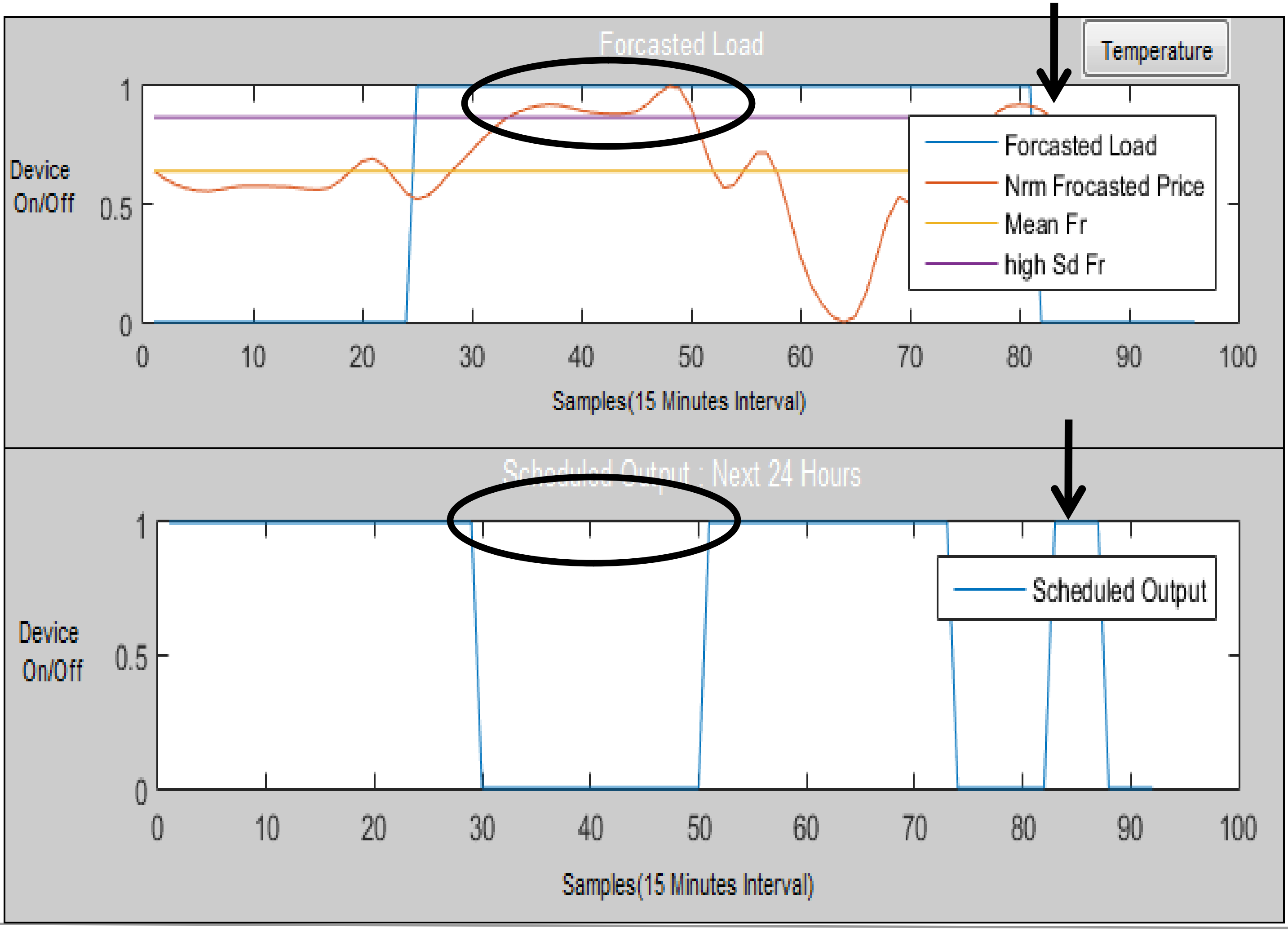
2) Present waited time

3) How Low is the present cost (This very Moment)

4) Alpha: state jumps

5) Total device execution time left

6) Checks, if device needs to be turned ON that day



Functionality : Heater

Heater : Forecast Date(April 29th of 2015)

1) Cost for next 1 hour

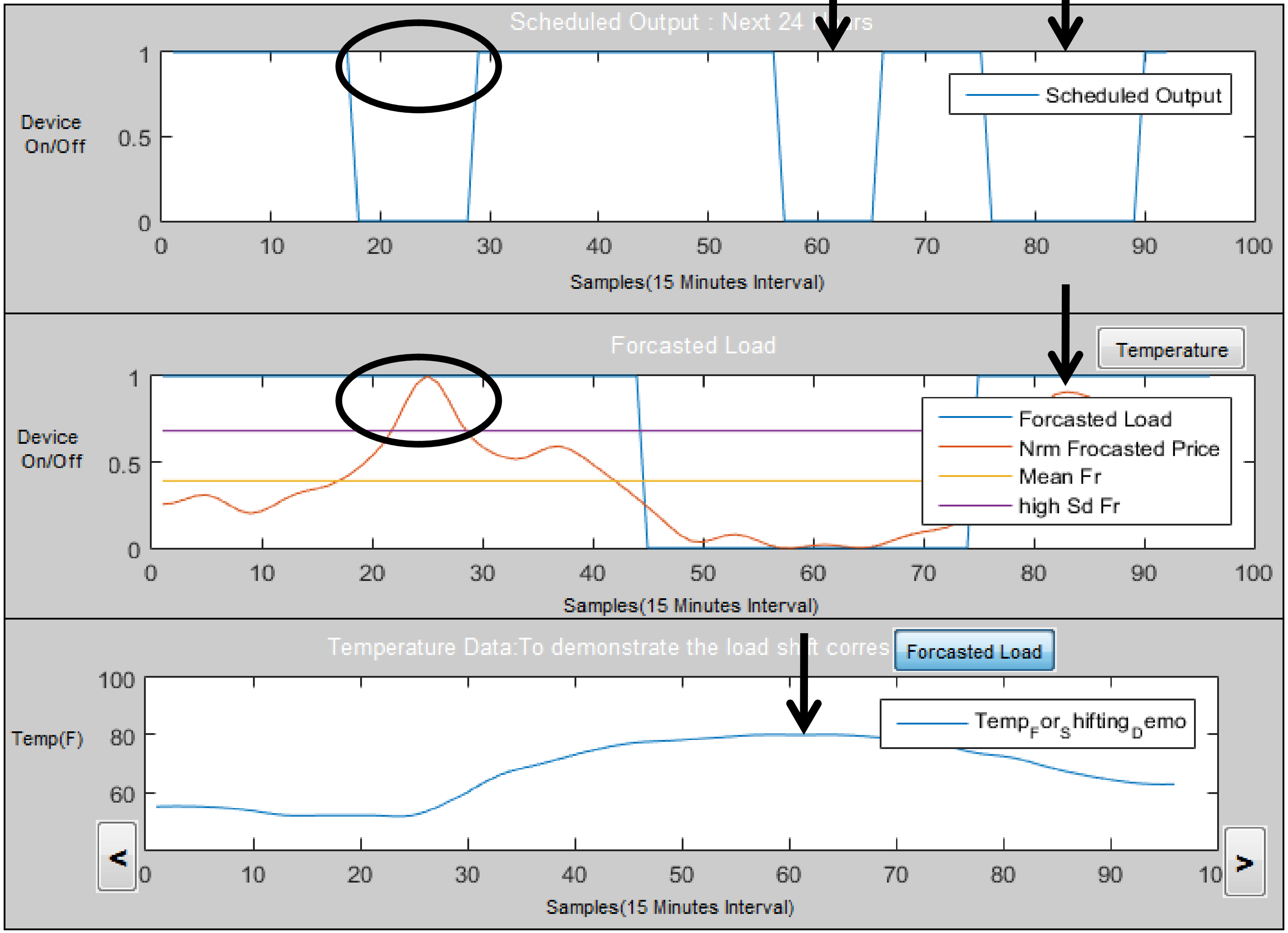
2) Present waited time

3) How Low is the present cost (This very Moment)

4) Alpha: state jumps

5) Total device execution time left

6) Checks, if device needs to be turned ON that day



Functionality : Cooler

Cooler: Forecast Date(April 29th of 2015)

1) Cost for next 1 hour

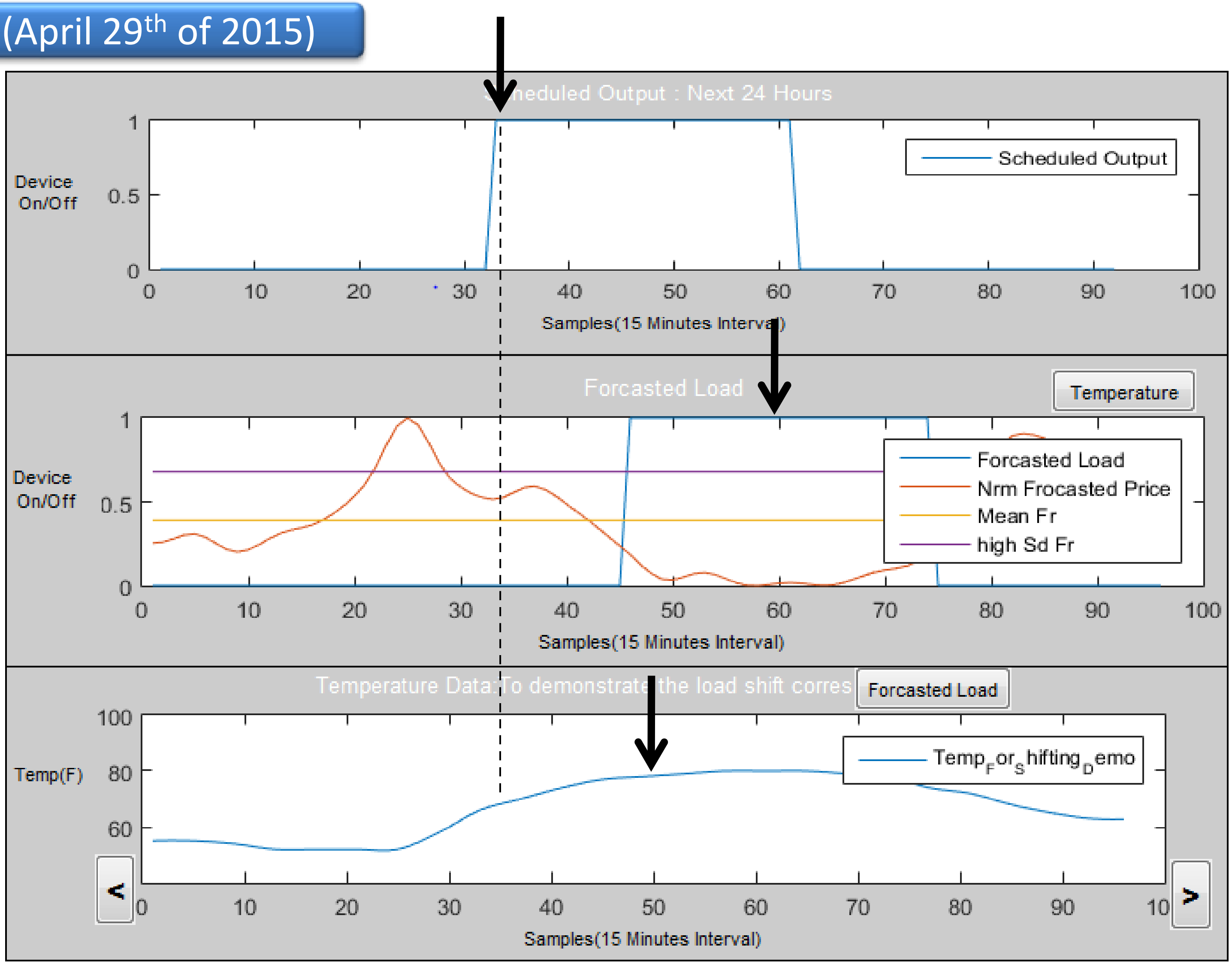
2) Present waited time

3) How Low is the present cost (This very Moment)

4) Alpha: state jumps

5) Total device execution time left

6) Checks, if device needs to be turned ON that day



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Performance Evaluation : Prediction

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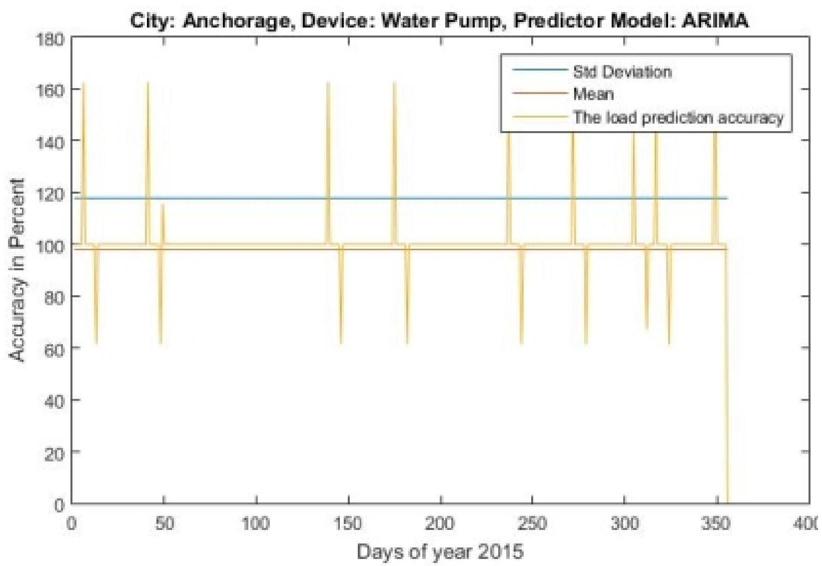
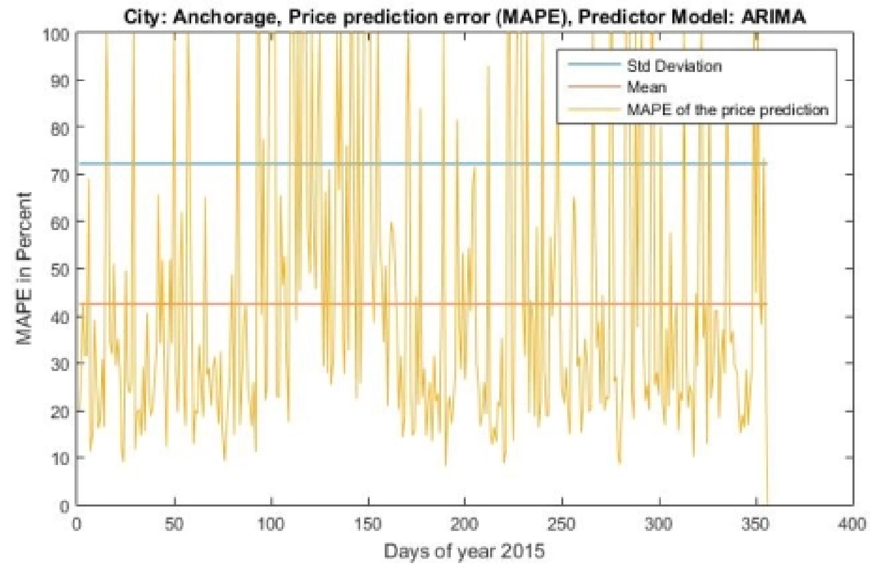
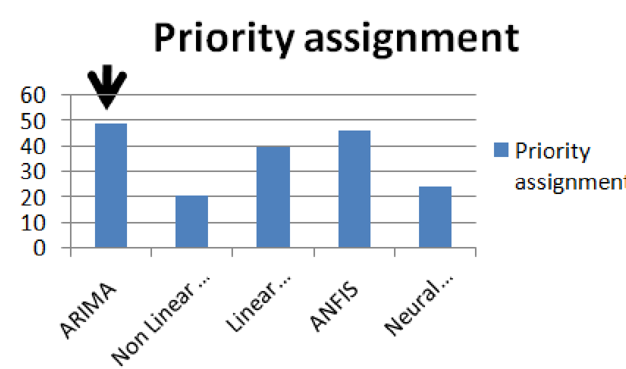




Water Pump	ANKORAGE		LITTLE_ROCK		PALMADEL	
	PRICE	LOAD	PRICE	LOAD	PRICE	LOAD
ARIMA	Mean:42.48 SD :72.72	Mean:97.94 SD : 115.76	Mean:42.84 SD :72.90	Mean:.97.94 SD : 115.76	Mean:42.73 SD :72.13	Mean:.97.94 SD : 115.76
Non Linear Regression	Mean:78.91 SD :109.79	Mean:97.92 SD : 115.83	Mean:78.91 SD :109.79	Mean:97.92 SD : 115.83	Mean:78.91 SD :109.79	Mean:97.94 SD : 115.86
Linear Regression	Mean:45.05 SD :75.07	Mean:97.80 SD : 115.90	Mean:44.81 SD :74.85	Mean:97.82 SD : 115.92	Mean:45.27 SD :75.27	Mean:97.80 SD : 115.90
ANFIS	Mean:42.41 SD :70.51	Mean:106.70 SD : 143.63	Mean:42.41 SD :70.51	Mean:106.70 SD : 143.62	Mean:42.41 SD :70.51	Mean:106.40 SD : 131.70
Neural Networking	Mean:54.30 SD :84.95	Mean:97.36 SD : 116.31	Mean:52.61 SD :83.39	Mean:97.28 SD : 115.63	Mean:52.36 SD :82.86	Mean:98.51 SD : 116.65

Prediction Accuracy Evaluation winner



Performance Evaluation : Optimization

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MDP Evaluation

	ANKORAGE					
	Water pump					
29-4-15	**Max Waiting Time (Samples 15 Min Interval)**	**Max Interruptions**	**MDP Scheduled ON Time (Samples 15 Min Interval)**	**Occurred ON Time (Without MDP) (Samples 15 Min Interval)**	**CoEC from MDP scheduled switching in cents**	**Occurred CoEC in cents**
ARIMA	20	2	57	57	1.2768	1.7046
Non Linear Regression	*Inf*	*Inf*	*Inf*	*Inf*	*Inf*	
Linear Regression	20	2	57	57	1.2979	
ANFIS	*Inf*	*Inf*	*Inf*	*Inf*	*Inf*	
Neural Networking	10	2	57	57	1.2934	

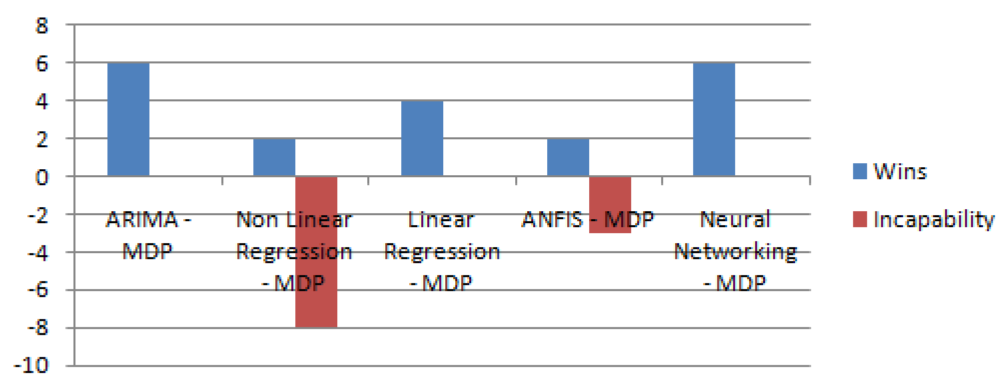


Table 1. *Majority winner by providing best price for different cenarios*

Inference of Performance Evaluation

Winners	USA_AK_ANKORAGE	USA_AK_LITTLE_ROCK	USA_AK_PALMADEL
Water Pump	ARIMA	ARIMA	ARIMA
Heater	ARIMA	ARIMA	ARIMA
Cooler	ARIMA	ARIMA	ARIMA

1) Cost for next 1 hour

2) Present waited time

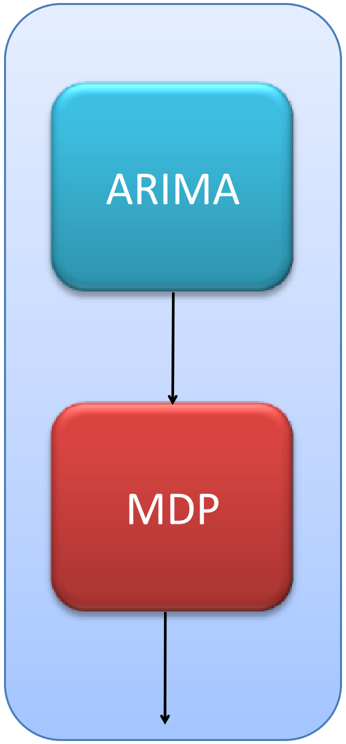
3) How Low is the present cost (This very Moment)

4) Alpha: state jumps

5) Total device execution time left

6) Checks, if device needs to be turned ON that day

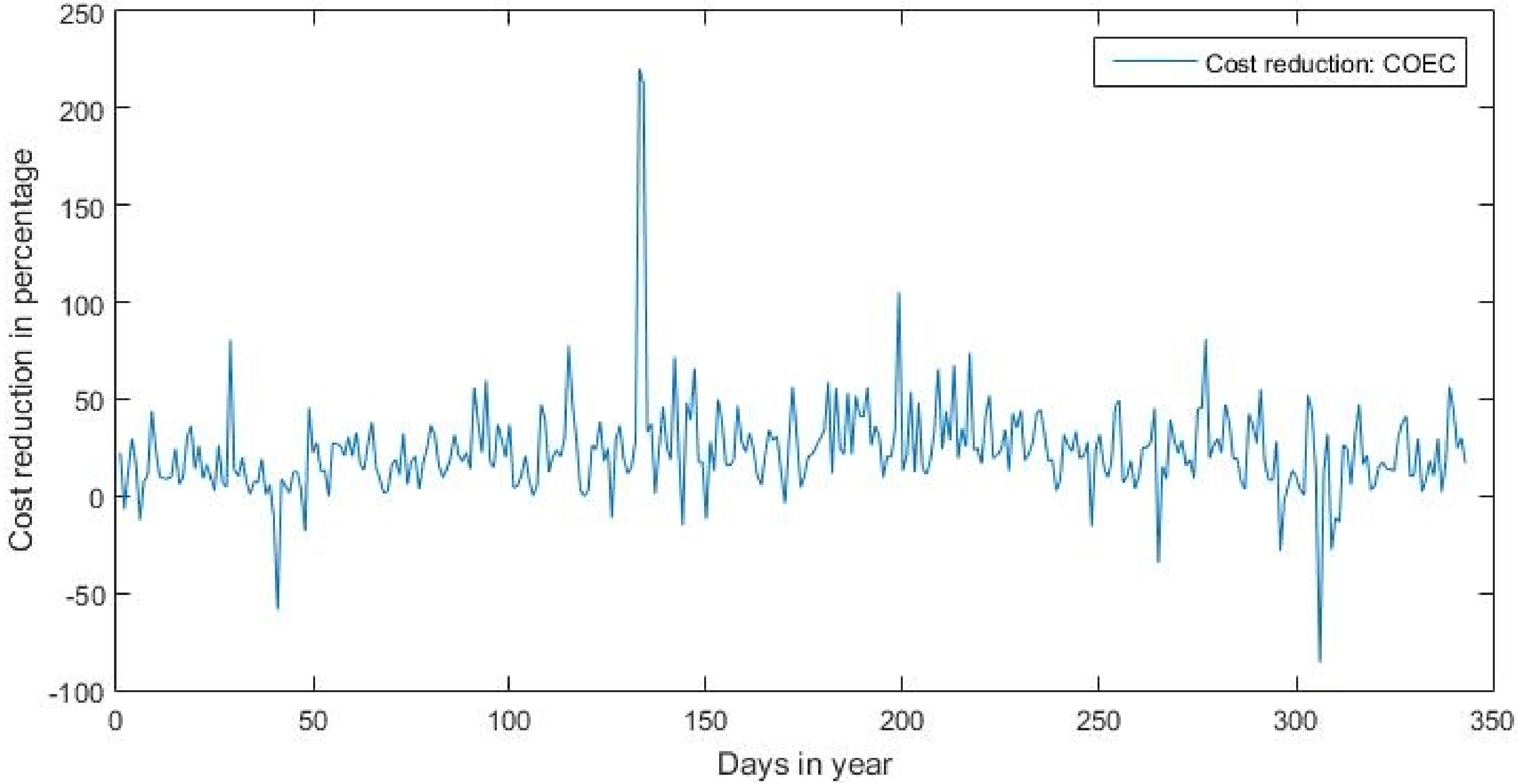
Best Fit Approach



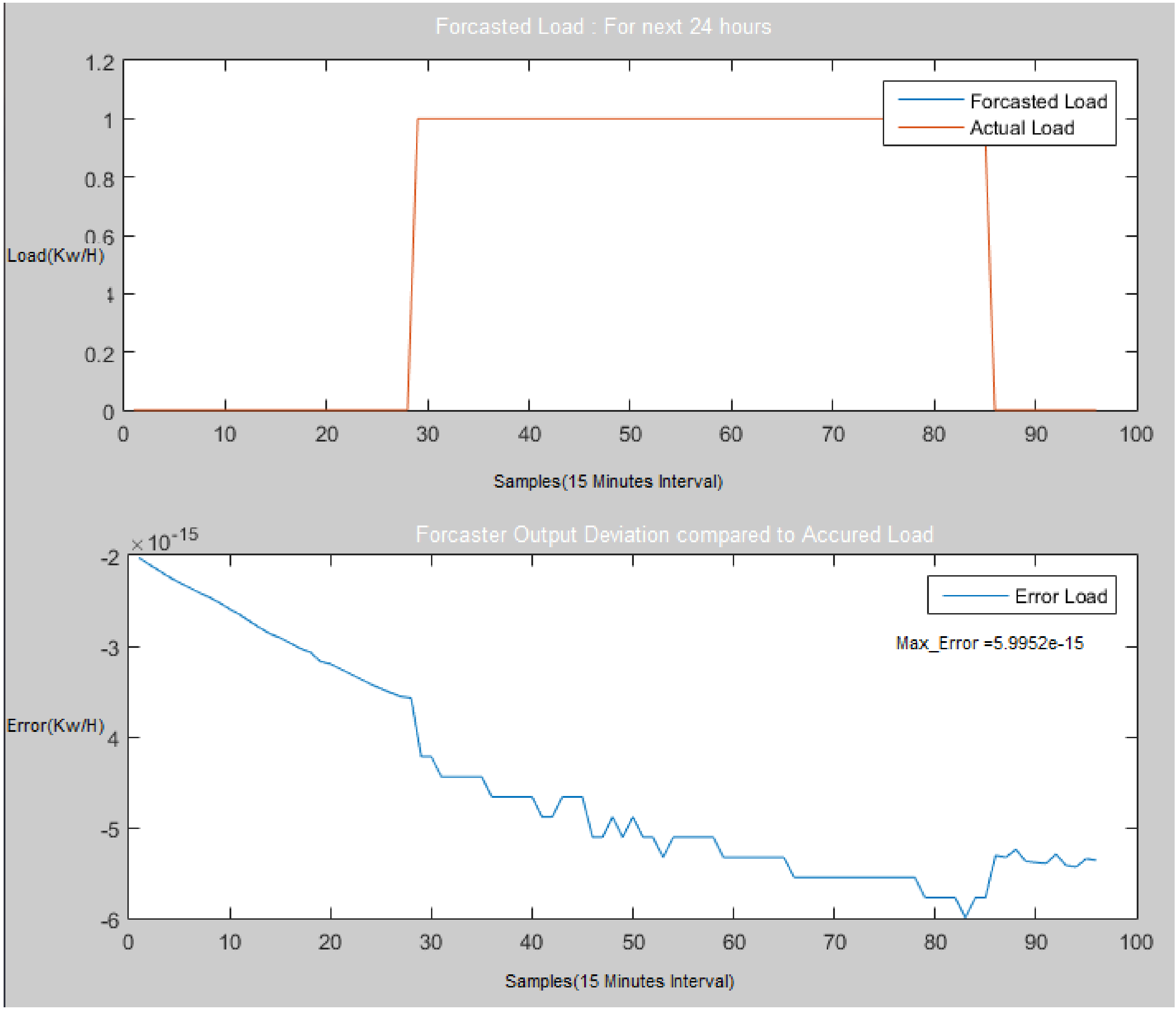
Scheduled Output For next 15 Min

THANK YOU

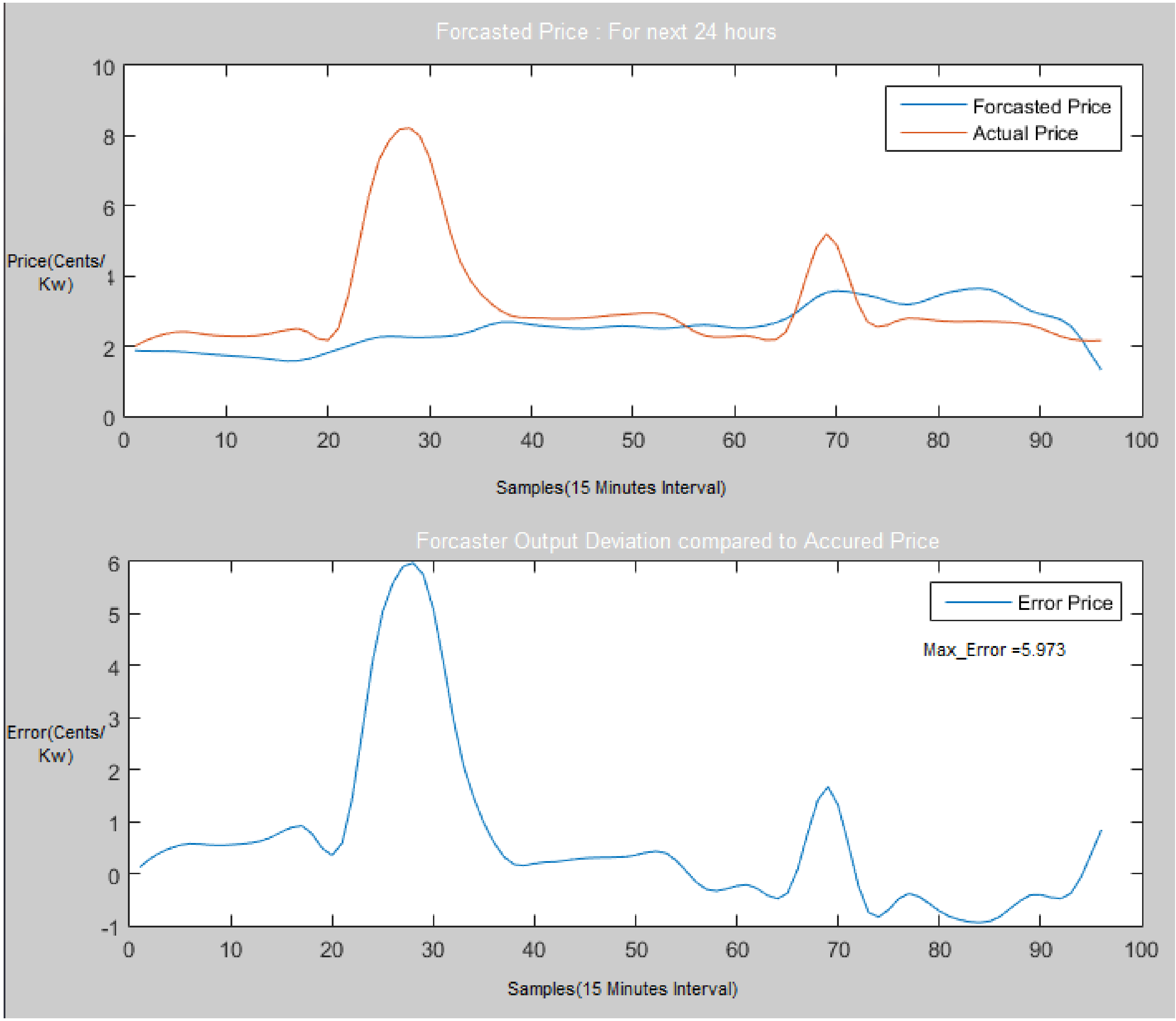
Key Plots : COEC or Cost reduction



Key Plots : Load prediction



Key Plots : Price prediction



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