

# Performance Modelling and Analysis of IoT based Edge computing policies

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## Research Article

**Keywords:** Distributed Architecture, Internet of Thing, Edge Computing, Resource management

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# **Performance Modelling and Analysis of IoT based Edge computing policies**

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## **ABSTRACT**

In today's era, the acceptance of IoT-based edge devices is growing exponentially, which creates challenges of data acquisition, processing, and communication. In the edge computing paradigm, intelligence is shifted from the center to the edge by performing specific processing and prediction locally. A strategy based on reducing communication resources between sensors and edge devices is the prime focus of this investigation. It uses a predictive model-based policy at edge devices for the reconstruction of not delivered context vector. A new hybrid Averaged Exponential Smoothening (AES) policy proposed is based on the current context vectors as well as a smoothing vector to reduce reconstruction error and improve the percentage of communication. It is observed that if we send data only when there is a marginal change in data then we can reduce communication overhead as well as keep reconstruction error low. This policy would be suitable for IoT-based edge computing applications for the smart city such as Smart Home, Healthcare, and Intelligent traffic to delivers the power of AI.

**Keywords:**Distributed Architecture, Internet of Thing, Edge Computing, Resource management

## **1. INTRODUCTION**

IoT is the heart of the digital business and a combination of operational as well as information technology necessary to create a business advantage. Gartner predicts that the high volume of significant business procedures and protocols will have some or other components of the IoT [1]. Data Analytics is fundamental to the accomplishment of IoT frameworks as they are the primary mainstay of the necessary decision making process. Real-time data and data analytics plays a crucial role in making a revolution.

There are different computing architectures available at the application layer. It mainly includes Cloud computing, Fog Computing, and Edge computing [2]–[4]. The new Architecture, like Edge Computing, addresses data management problems by leveraging analytics at the different layers from the sensor to the edge of the network. There are a network of sensors and actuator within an enterprise which generate, manage, and analyze such big data which has massive challenges. In an edge computing model, sensors and Actuators transmit or receive data to a close-by edge gateway like a switch that checks or analyzes the data instead of forwarding it to the cloud. By moving insight from a center incorporated cloud to an edge of an enterprise can be made nearer to where they have happened. Edge computing can help to illuminate latency challenges and empower organizations to open doors utilizing a distributed computing

architecture [5]–[8]. A smart IoT network incorporates policies to push information preparation and management of application data to the edge of the net. This new architecture is used to perform advanced analytics at the point where the data generate or most actionable. With a smart deployment strategy, decision-makers get visual and easily-understood insights of data in near real time. In Edge computing, advanced analytics deploys on the end device (Sensor and Actuating Devices), on the gateway (Edge Devices), and in the cloud, giving secure and instant insight into the time and place it most needed.

A variety of IoT-based edge architecture models can be explored in the literature. Here three-layered edge computing model consisting of the core, edge, and sensor layers is used, as shown in figure 1. As we move from the sensor layer to the core layer the latency goes on increasing. So it is better to do time-sensitive analytics in the edge or sensor layer instead of pushing it to the core layer.

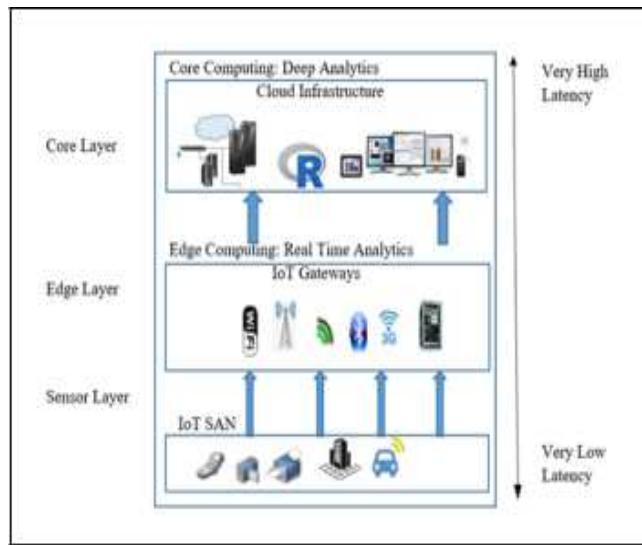


Figure 1. IoT system Architecture

- **Sensor Computing** - The sensor layer consists of IoT sensors, which include motion, light, temperature, humidity, and many more. It consists of smart wireless sensors and actuators, which are having limited computing capabilities. Sensors monitor the surrounding environment and asset state.
- **Edge Computing** - It includes sensor data aggregation systems using gateway devices. The edge layer consists of gateway devices that receive the data and aggregates it and transfer it to the core computational layer. This layer acts as an intermediary layer that aggregates from lower layers and forwards it to the core layer for further processing.
- **Core Computing** - It uses to manage, store, analyze, and build a programming model of data. The core computational layer consists of high-end machines for storing, computing, and analyzing the sensor data to generate actionable information. This information transmits to the user via the IoT gateway.

Section II briefs about related work, architecture, edge computing models, and parameters for analysis. In part III, the main focus is on the proposed policy. Section IV shows the experimental study and result from analysis, whereas section V depicts a summary and open research challenges in edge computing.

## 2. LITERATURE REVIEW

There are many research papers available that attention problems on different IoT scenarios and explored cutting edge technologies. Many paper [9]–[14] gives observations of IoT, different empowering innovations, advantages of its utilization, different applications, and significant investigation issues. An enormous number of IoT empowering techniques including design, detecting, and innovative technologies are examined in [15]–[19]. Paper [20]–[22] presents a survey of IoT research challenges applications and technologies. Many researchers [23]–[28] discussed heterogeneous inter-operability of different devices and information, self-variation, security, and energy enhancement strategies. The application rundown of the vast majority of the study papers is for the most part identified with controlling and observing in the modern, cultural, and ecological areas [29]–[33]. Registering, correspondence and ID innovation, security, protection, trust, conveyed engineering, and their difficulties examine in de-tail [34]–[40]. These papers [41]–[44] clarifies in detail the study, applications, advances, finished ventures, issues, and challenges.

### 2.1 Background

In the traditional IoT system, the sensing node senses the environmental parameters and sends it to the centralized system to process it further to analyze the situation. It per-forms analytics tasks only on back end devices and not on Sensor or Actuation Device(SAD) or network gateway Edge Device(ED) [45]. Nowadays, these devices are increasing with computing capacity, which can perform some processing of data at SAD or/and ED of the network. This processing eventually can reduce the energy required for transmitting data to the centralized system, bandwidth requirement, high latency, and the prolonged lifetime of the sensor network, which encourages edge analytics. Edge Computing architecture either pushes intelligence to ED for analytics or to SAD, where both collaboratively support edge analytics, as shown in figure 2.

All SADs coordinates with ED, who is responsible for keeping track of data generated and energy consumption on communication between SAD and ED, as well as local computation on ED. It is considered that cost of handling and investigation at ED is nontrivial, and one should consider the balance between intra edge-network communication and local computation. The prediction capability results in the SAD<sub>i</sub> ready to conclude whether to send or not generated vectors  $x_t$  to ED<sub>j</sub>. SAD<sub>i</sub> relies on a threshold of error -based delivery decision rule based on a couple of cases as follows:

TABLE I : Terminology and Notation

$SAD_i$	Sensor or Actuation Device i
$ED_j$	Edge Device j
$x_t$	original context vector is data generated at the sensor device
$\hat{x}_t$	predicted context vector at the sensor device
$u_t$	reconstructed context vector at Edge device

et	error is the difference between the originally predicted context vector at the se
$\hat{y}_t$	predicted or forecast context vector
$\theta$	threshold for error(e) at time (t)
$\alpha$	smoothing parameter of prediction
$s_t$	smoothing vector at the edge device

- **Case 1:** If the difference between model based predicated value  $\hat{x}_t$ , and the sensed context vector  $x_t$ , is more than a threshold of error, i.e.,  $et > \theta$ , then the SADi send the original context vector  $x_t$  to the EDj.
- **Case 2:** if  $et \leq \theta$ , then SADi won't send  $x_t$  to the EDj so EDj is responsible for the reconstruction of context vector for further processing. This reconstruction of the context vector at EDj is achieving with various ways or policies, as shown in the next section.

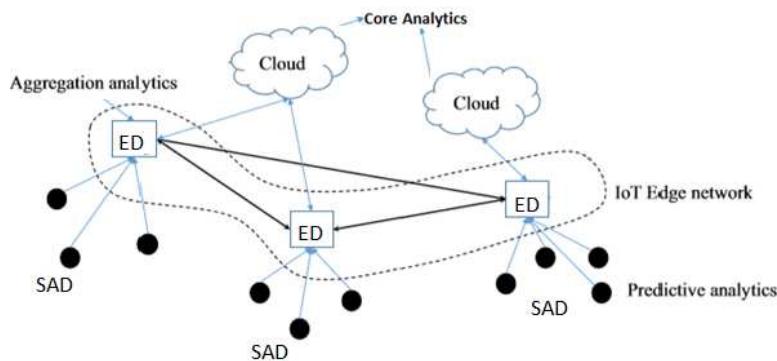


Figure 2. Edge network with Sensor Actuator Devices and Edge Devices

### 3.2 Related Work

Many edge computing-based data models are available in the literature, which analyzes time-series data coming from sensors by keeping simplicity and complexity in mind. The various policies based on edge computing models for selective data forwarding [45] are as follows.

- Random walk Model - This is the simplest and easiest model used for time-series forecasting. In this case, the reconstruction of data depends on the previous observation.

$$\hat{y}_{T+h|T} = y_T$$

where it denotes forecast data after h interval.

- Simple average Model - In this model, the reconstruction of data depends on an average of sliding window-based stream data.

$$\hat{y}_{T+h|T} = \frac{1}{T} \sum_{t=1}^T y_t$$

where data  $y_1, \dots, y_T$  denotes historical data.

- Simple Exponential Smoothing (SES) model - This is the most widely and successfully used forecasting model. In this model, the reconstruction of data depends on weighted averages of previous data of  $N$  observations based window. This weightage depends more on recent data than older data. This scheme applies to data with no clear trend and seasonal pattern.

$$\hat{y}_{T+1|T} = \alpha y_t + (1 - \alpha)y_{t-1} \dots$$

Where  $\alpha$  it is a smoothing parameter.

### 2.3 Parameters for Analysis

Various measures used for the evaluation of different models are listed below. The precision of each model is essential from the evaluation point of view.

- Communication efficiency - It refers to the efficiency of communication resources to reduce delays.

$$c(T) = \sum_{t=1}^T \sum_{i=1}^n I_{i,t}$$

Where  $I_{i,t} = 1$  if SADi send its sensed value to the ED otherwise  $I_{i,t} = 0$

- Root Mean Square Error (RMSE) - It is the square error between the actual context vector and reconstructed one calculated as follows:

$$RMSE = \sqrt{\text{mean}(e_t^2)}.$$

- Mean Absolute Error (MAE) - It is an absolute error between actual context vector and reconstructed one calculated as follows:

$$MAE = \text{mean}(|e_t|)$$

- Mean Absolute Percentage Error (MAPE) - It is an absolute percentage error between actual context vector and reconstructed one calculated as follows:

$$MAPE = \text{mean}(|p_t|)$$

The next section shows the proposed edge computing policy and its performance based on evaluation parameters.

## 3. PROPOSED EDGE COMPUTING POLICY

The proposed policy takes advantage of the Exponential Smoothing Model and averaged Model to come up with a scheme of Averaged Exponential Smoothing (AES) Policy as given in figure

3, where the context vector reconstructed at ED<sub>j</sub> with the combination of averaged and exponential smoothing models. There are two possibilities in the reconstruction of context vector using sliding window maintained at ED<sub>j</sub>. In the first case, the ED<sub>j</sub> directly inserts the received context vector in the sliding window and removes the oldest one, and finds value based on the recent received vector and previous vector. In the second case, ED<sub>j</sub> reconstructs the value with the average of smoothed context vector and most recently received context vector, and removes the oldest value.

$$\hat{y}_{T+1|T} = \frac{u_{t-1} + s'_{t-1}}{2}$$

where  $s'$  t-1 smoothing vector constructed at edge device, which can be different than the smoothing vector at the sensor device.

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**Algorithm 1 AES Policy**

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**Data:** Sliding Windows  $W_{ij}$  at ED  $j$  for each connected SAD  $i$

**Result:** Reconstruction of context vector at ED  $j$  for each connected SAD  $i$

```

for SAD  $i \in N_j$  do
    if  $e_{i,t} > \theta_t$  then
        SAD  $i$  sends  $x_t$  to ED  $j$ 
         $s'_t = \alpha x_t + (1-\alpha)s'_{t-1}$ 
    else
        /*Reconstruction by local current average context
        vector and one-step ahead forecasting*/
         $u_t = \text{mean}(u_{t-1}, s'_{t-1})$ 
         $s'_t = s'_{t-1}$ 
    end
    /*Update the sliding window*/
     $W_{ij} = W_{ij} - u_{t-N}$ 
     $W_{ij} = W_{ij} \cup u_t$ 
end

```

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Figure 3. AES policy

Since this policy combines two different models, it removes the bottleneck of both the systems and improves the performance and reduces reconstruction error significantly. The next section demonstrates an experimental study based on edge computing models, parameters, and analysis of experimental results.

#### 4. EXPERIMENTAL RESULTS

In the previous section, an examination of different edge computing models from a theoretical point of view is discussed. Their performance on a benchmark dataset and the experimental dataset is available for empirical evaluation.

In the experiment, the real-time use of two datasets to assess the evaluation of the proposed policy, as shown in Table 1. The first dataset is available on the University of California Irvine (UCI) repository [46]. These data are collected every hour and refer to  $T = 9357$  12-dimensional measurements with  $n = 12$  SADs and one ED. This dataset has missing values that are replaced by the mean of that attribute. The second datasets have been collected from an experimental setup in the lab for collecting data from a different sensor like temperature, humidity, and Carbon

Monoxide(CO), These data are collected every 5 mins and refer to  $T = 1441$  3-dimensional measurements with  $n = 3$  SADs and one ED.

Table II: Description of Data-Set

Name	Instances	Attributes	Type of Sensor
Air Quality	9357	12	CO PT08.S1 (tin oxide) Non Metallic HydroCarbons Benzene PT08.S2 (titania) PT08.S3 (tungsten oxide) NO2 PT08.S4 PT08.S5 (indium oxide) Temperature Relative humidity Absolute humidity
Sensor Data	1441	3	Temperature Relative humidity CO

All three existing policies and proposed policy implemented using the R platform, and the results were analysed for prediction error, reconstruction error, and percentage of communication.

- Policy 1: This random walk model-based policy reconstructs the data based on the recently acquired context vector. The reconstructed data pushed to the sliding window and the previous data from the window removed.

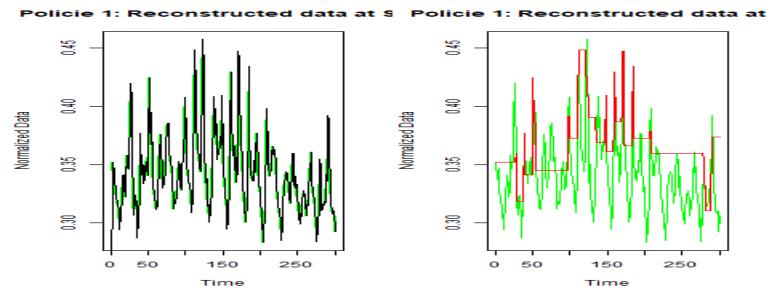


Figure 4. Policy 1 based Reconstructed data for DS1

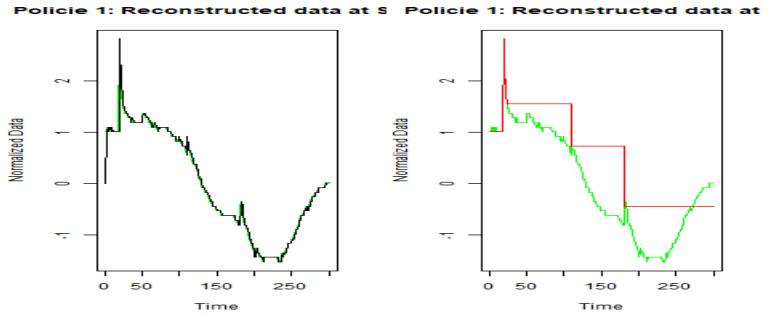


Figure 5. Policy 1 based Reconstructed data for DS2

- Policy 2: This averaged model-based policy reconstructs the data not delivered context vector at ED as the average of data available for consideration in the window at ED, i.e., this reconstructed data is pushed to the window discarding the earliest one.

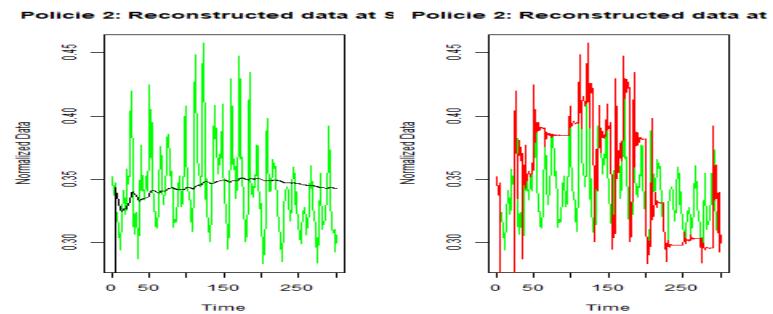


Figure 6. Policy 2 based Reconstructed data for DS1

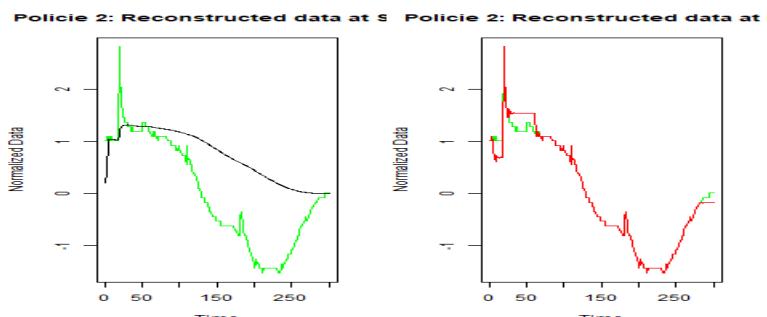


Figure 7. Policy 1 based Reconstructed data for DS2

- Policy 3: This SES model-based policy reconstructs the undelivered context vector at the ED in two ways. ED either fills in the given context vector into the window and removes the earliest context vector and recalculates the smoothing parameter based on the delivered context vector or it reconstructs the new smoothed context vector and removes the previous context vector from the window.

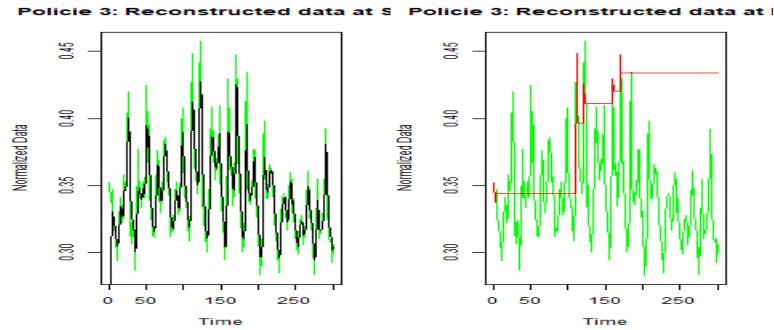


Figure 8. Policy 3 based Reconstructed data for DS1

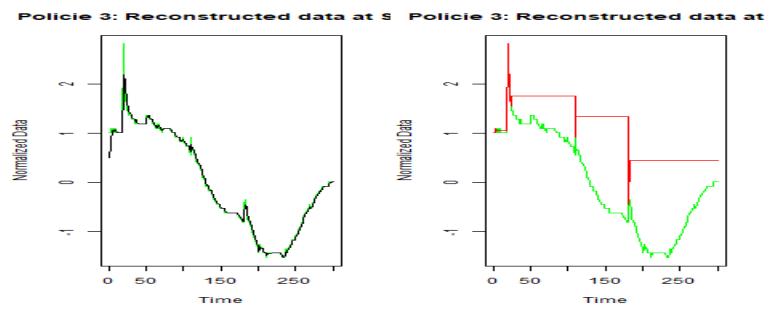


Figure 9. Policy 1 based Reconstructed data for DS2

- Policy 4 (AES): This proposed policy applies an average of the exponential smoothing vector and previously received context vector for reconstructing the not delivered context vector in the ED. ED either fills in the given context vector into the window and removes the earliest context vector and recalculates the smoothing parameter based on delivered context vector. Or it reconstructs the context vector with the average of recent smoothing parameter and previously received context vector and removes the earliest data from the sliding window. The comparison of all policies as shown in figure 12 and figure 13 for DS1 and DS2, respectively.

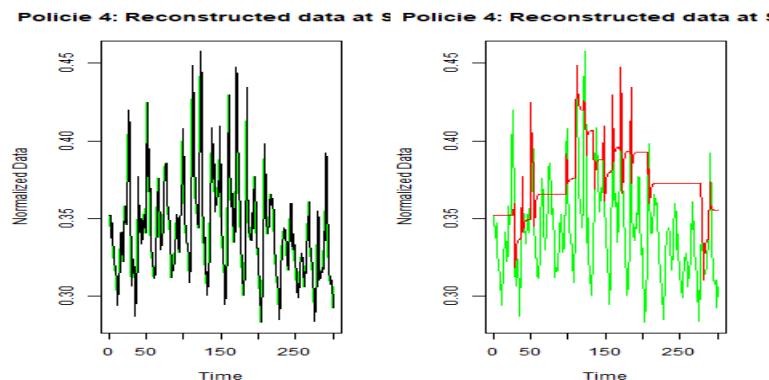


Figure 10. Policy 3 based Reconstructed data for DS1

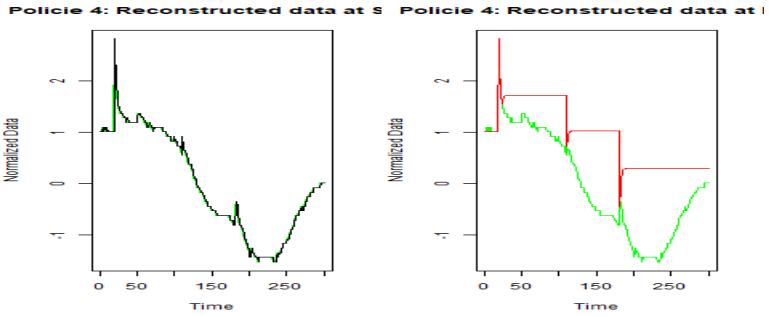


Figure 11. Policy 1 based Reconstructed data for DS2

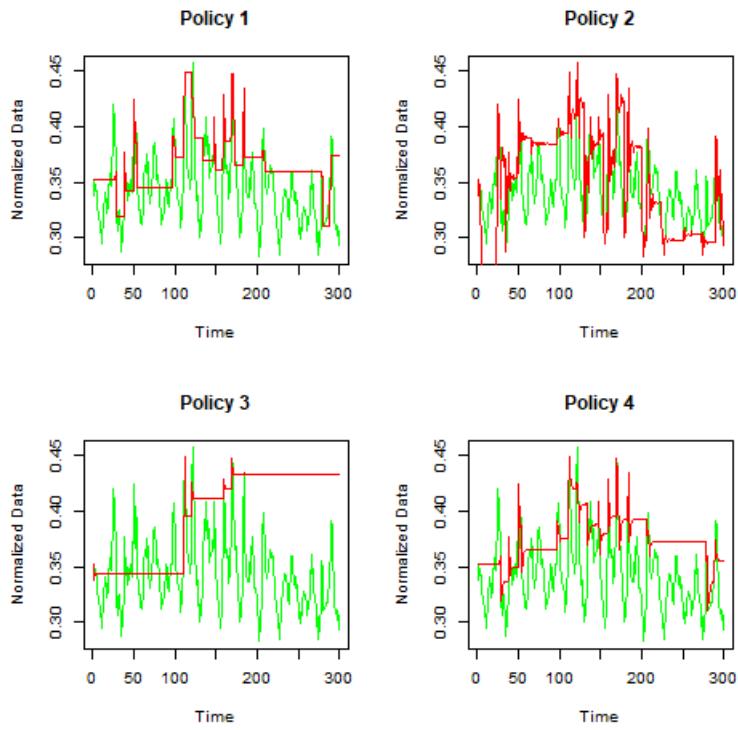


Figure 12. All Policies based Reconstructed data for DS1

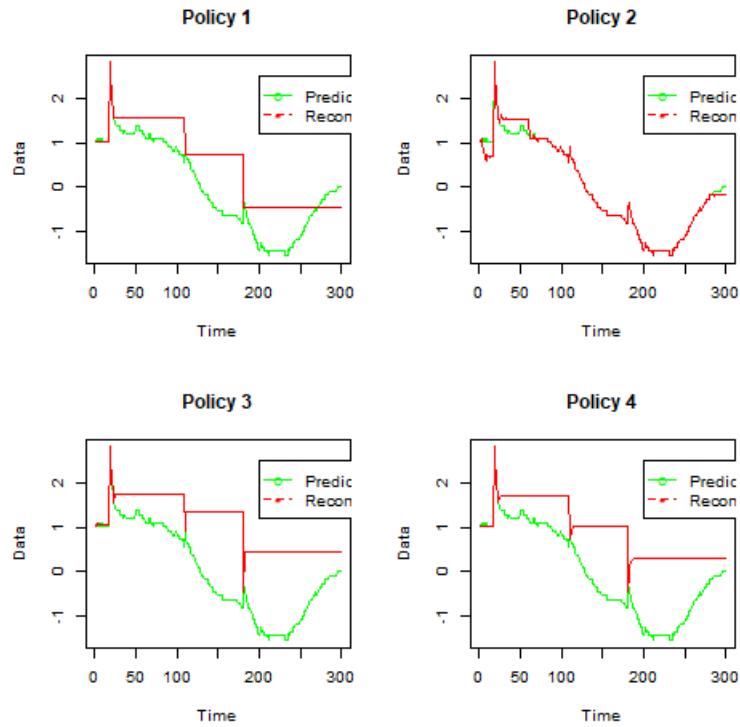


Figure 13. All Policies based Reconstructed data for DS2

TABLE III: Analysis of All Policies for Ds1

Policy Name	Prediction Error	Reconstruction Error	Percentage of communication
Policy 1	5.639810	160.074095	96.66
Policy 2	298.368985	4.880959	23.66
Policy 3	1.667822	478.698995	97.00
Policy 4(AES)	4.627129	364.224430	95.00

TABLE IV: Analysis of All Policies for DS2

Policy Name	Prediction Error	Reconstruction Error	Percentage of communication
Policy 1	0.241479	0.398363	7.177852
Policy 2	0.447277	0.605774	15.159423
Policy 3	0.082573	1.727653	10.385850
Policy 4(AES)	0.117307	0.558918	5.873716

It is clear from Table III and Table IV that AES policy is performing better than other policies for both dataset in terms of reconstruction error, and the percentage of communication because it is based on the current context vector as well as smoothing vector.

## 5. CONCLUSION

The usage of IoT devices has been growing exponentially with time. The traditional policies are not sufficient to address the issues of IoT devices such as data acquisition, processing, communication, privacy security. Considering these limitations of centralized processing in the growing era of IoT devices, a distributed policy was needed. Therefore, in this paper, a distributed and lightweight AES model is proposed. The proposed model design to reduce communication overhead and, in-turn to minimize the energy of processing requirements. It compares with existing policies, which shows that the AES model performs better than existing models regarding the percentage of communication. Future work includes the investigation of intelligent techniques for minimization of prediction and reconstruction error by offloading computing to the next level.

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**Code Availability:**

There is no code availability.

**Author's contribution:**

There is no author's contribution.

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# Figures

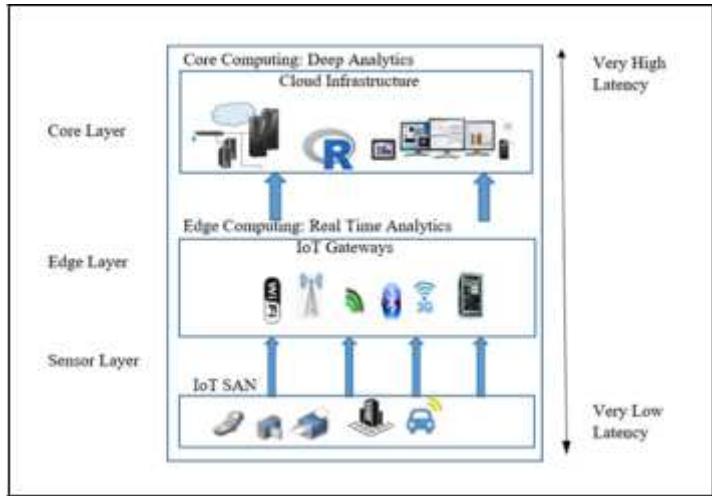


Figure 1

IoT system Architecture

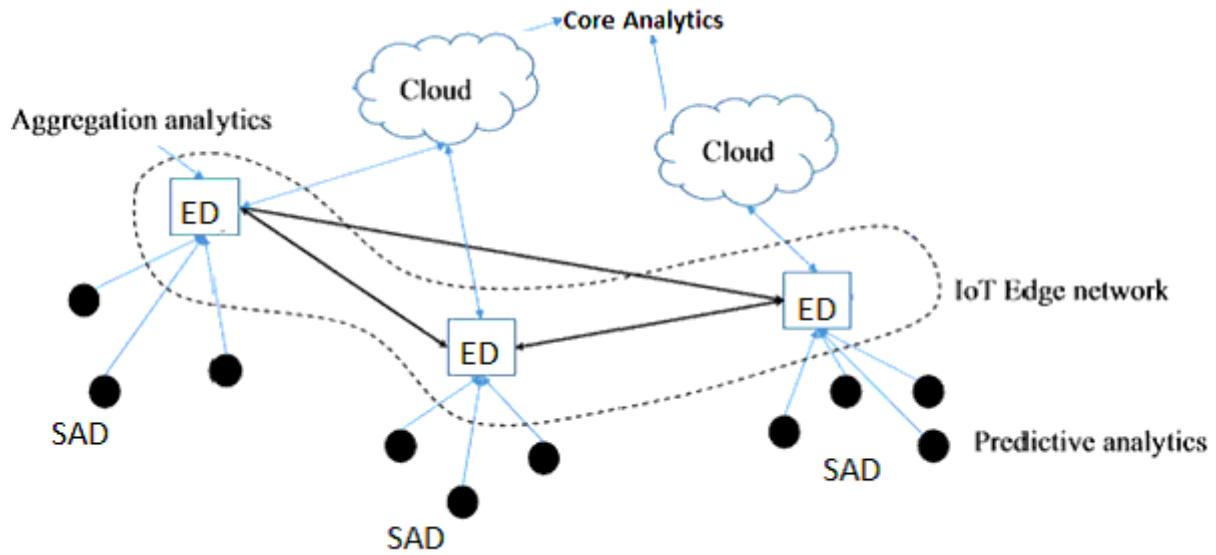


Figure 2

Edge network with Sensor Actuator Devices and Edge Devices

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**Algorithm 1** AES Policy

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**Data:** Sliding Windows  $W_{ij}$  at ED j for each connected SAD i

**Result:** Reconstruction of context vector at ED j for each connected SAD i

**for** SAD  $i \in N_j$  **do**

**if**  $e_{i,t} > \theta_t$  **then**

        SAD i sends  $x_t$  to ED j

$$s'_t = \alpha x_t + (1-\alpha)s'_{t-1}$$

**else**

        /\*Reconstruction by local current average context vector and one-step ahead forecasting\*/

$$u_t = \text{mean}(u_{t-1}, s'_{t-1})$$

$$s'_t = s'_{t-1}$$

**end**

    /\*Update the sliding window\*/

$$W_{ij} = W_{ij} - u_{t-N}$$

$$W_{ij} = W_{ij} \cup u_t$$

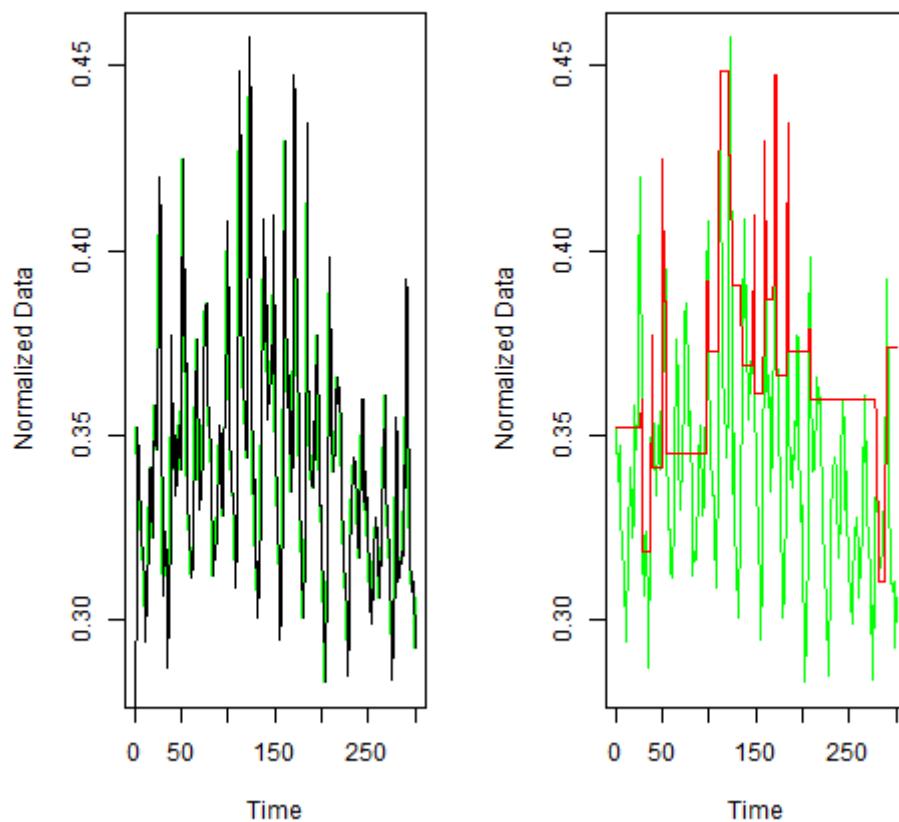
**end**

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Figure 3

AES policy

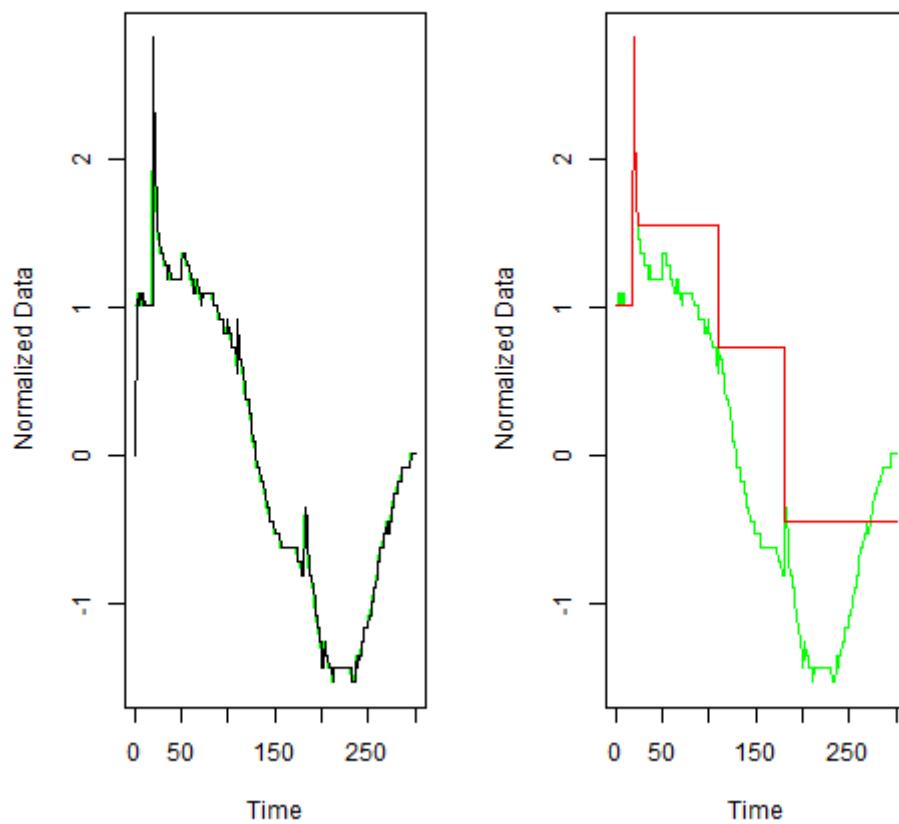
**Poliec 1: Reconstructed data at S Policie 1: Reconstructed data at I**



**Figure 4**

Policy 1 based Reconstructed data for DS1

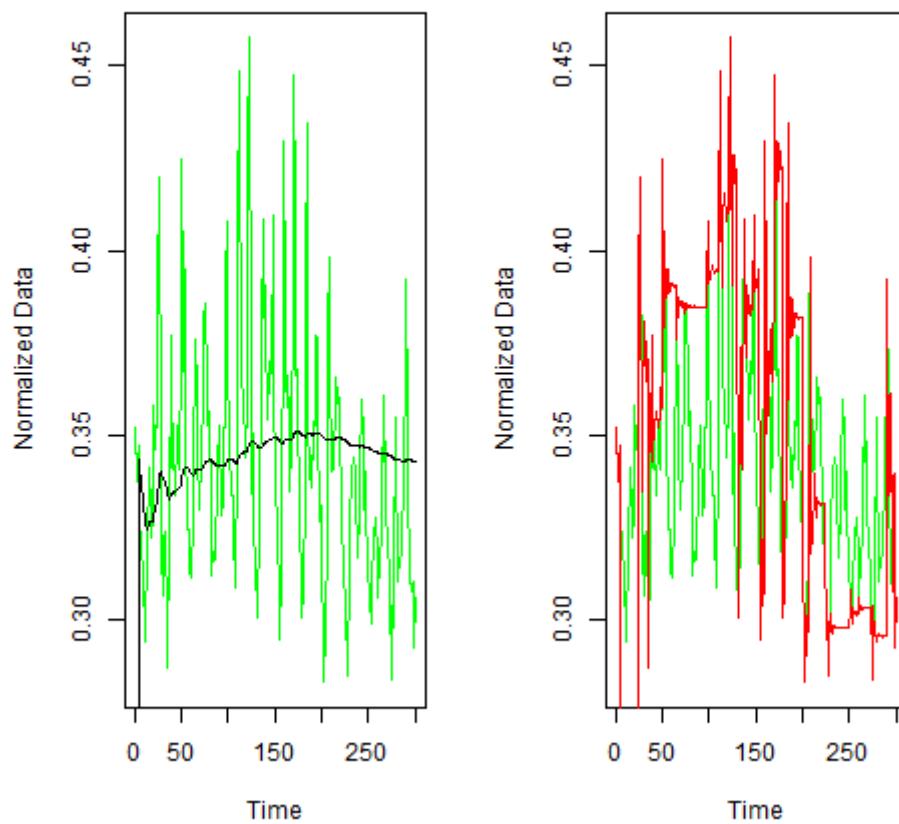
**Poliec 1: Reconstructed data at S Policie 1: Reconstructed data at I**



**Figure 5**

Policy 1 based Reconstructed data for DS2

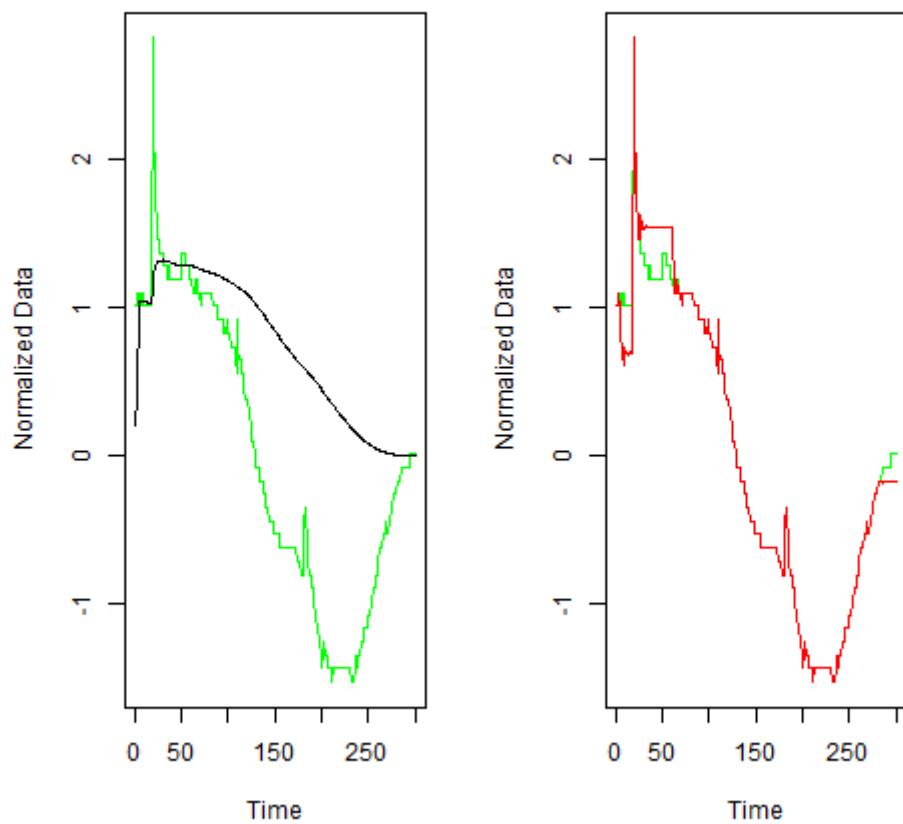
**Poliec 2: Reconstructed data at S Policie 2: Reconstructed data at I**



**Figure 6**

Policy 2 based Reconstructed data for DS1

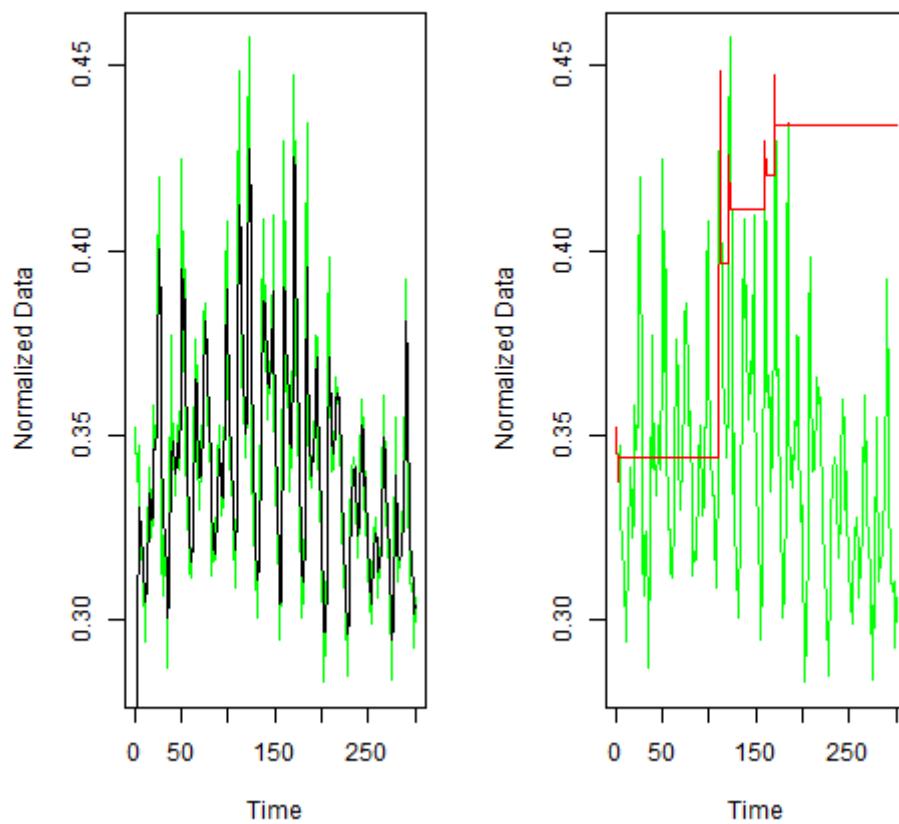
**Poliec 2: Reconstructed data at S Policie 2: Reconstructed data at I**



**Figure 7**

Policy 1 based Reconstructed data for DS2

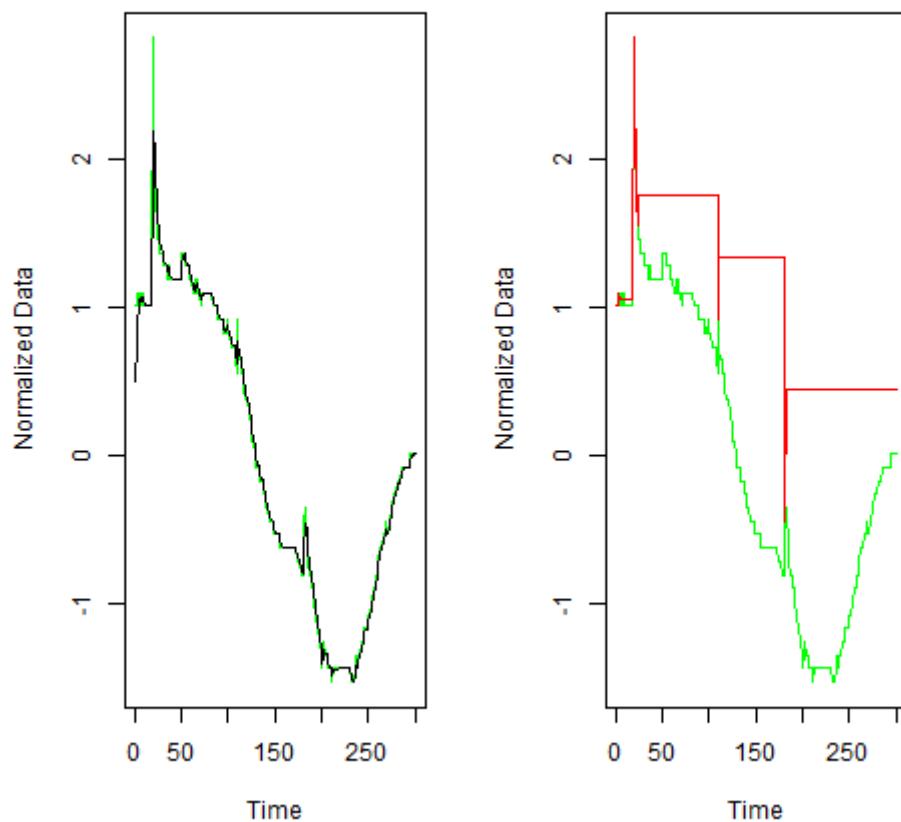
**Poliec 3: Reconstructed data at S Policie 3: Reconstructed data at I**



**Figure 8**

Policy 3 based Reconstructed data for DS1

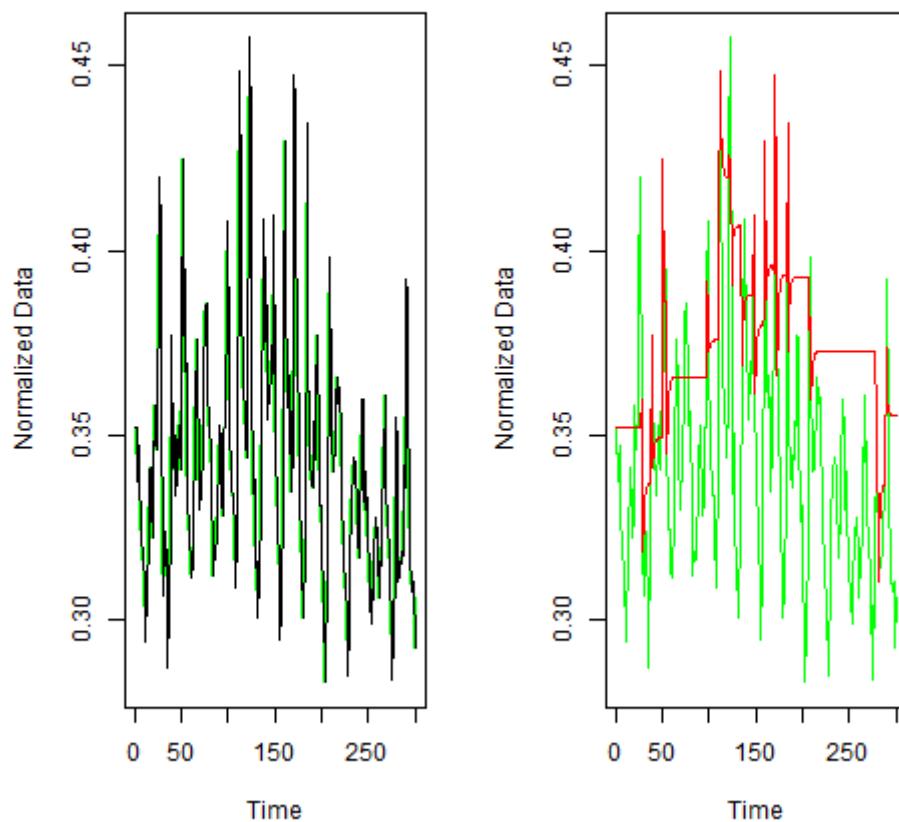
**Poliec 3: Reconstructed data at S Policie 3: Reconstructed data at I**



**Figure 9**

Policy 1 based Reconstructed data for DS2

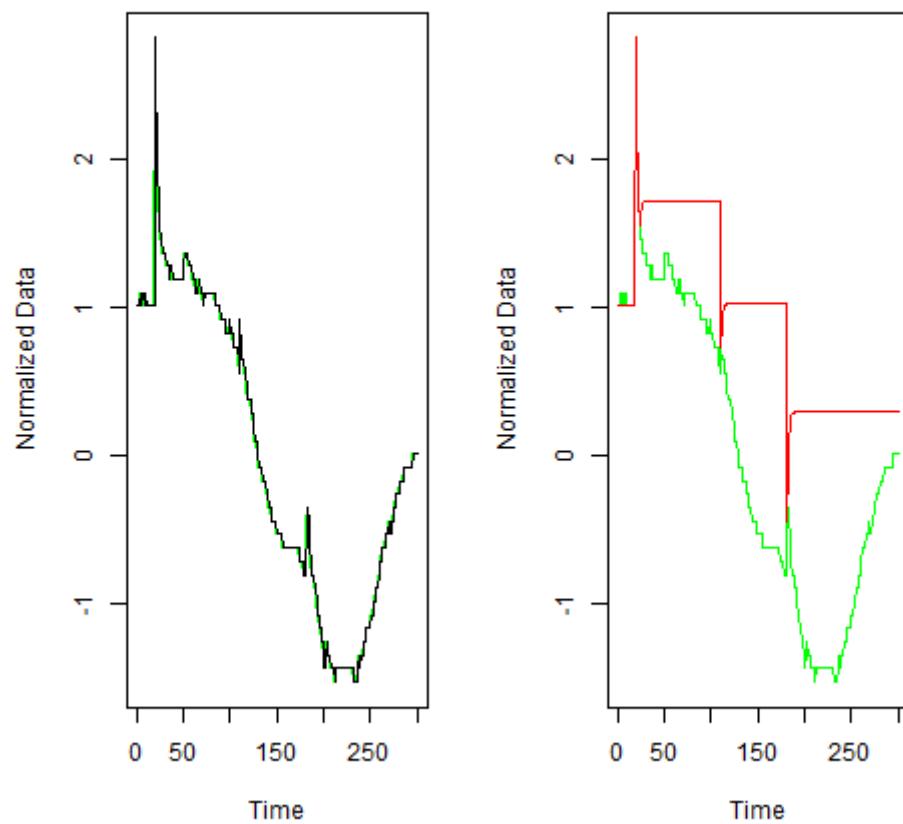
**Poliec 4: Reconstructed data at S Poliec 4: Reconstructed data at S**



**Figure 10**

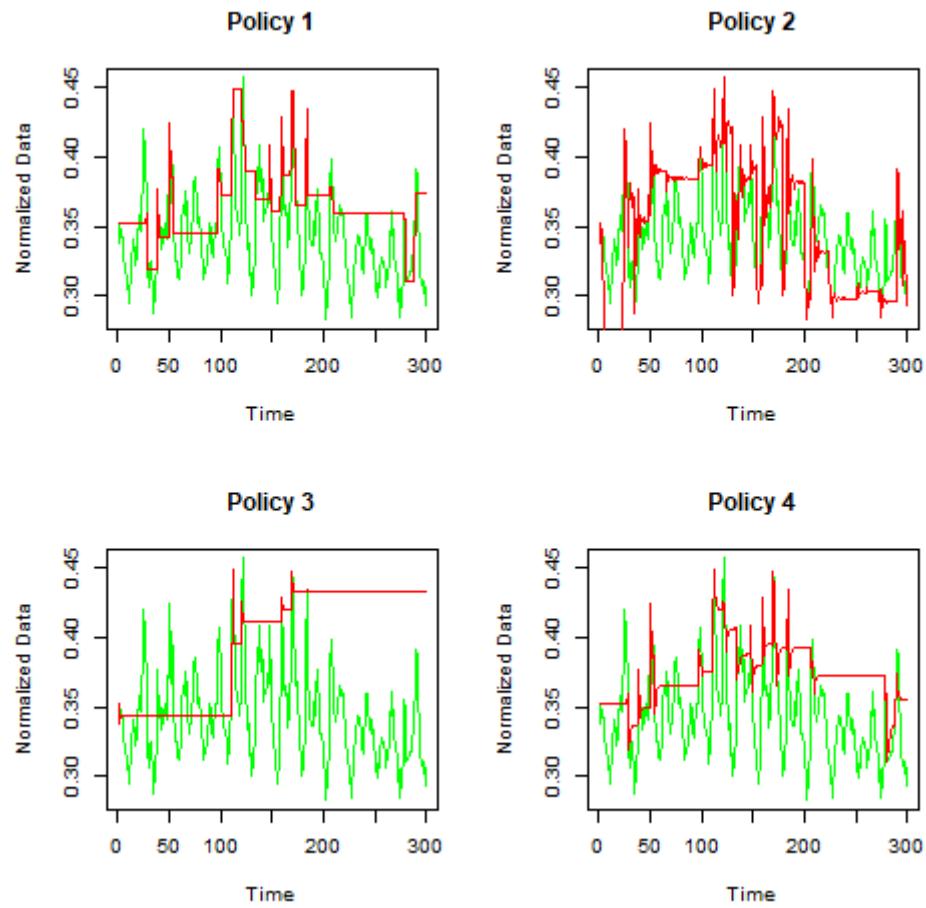
Policy 3 based Reconstructed data for DS1

**Poliec 4: Reconstructed data at S Policie 4: Reconstructed data at I**



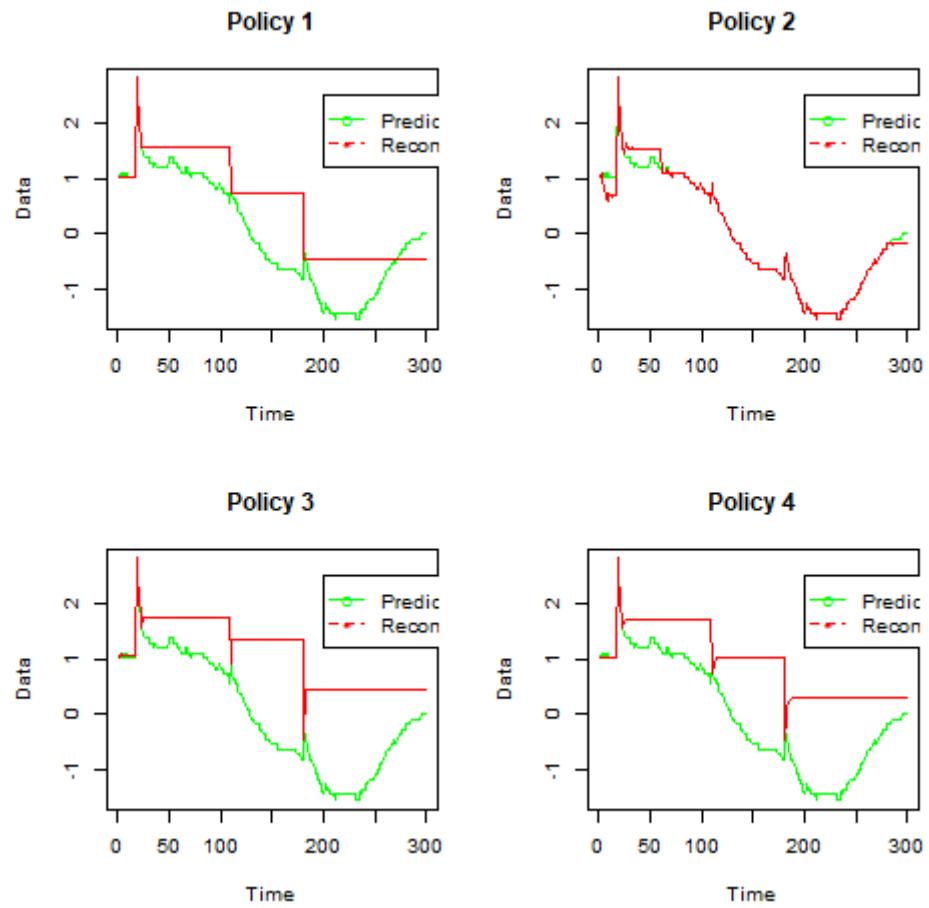
**Figure 11**

Policy 1 based Reconstructed data for DS2



**Figure 12**

All Policies based Reconstructed data for DS1



**Figure 13**

All Policies based Reconstructed data for DS2