A NOVEL SMART ENERGY THEFT SYSTEM (SETS) FOR IOT BASED SMART HOME

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Abstract—In the modern smart home, smart meters and Internet of Things (IoT) have been massively deployed to replace traditional analogue meters. It digitalises the data collection and the meter readings. The data can be wirelessly transmitted that significantly reduces manual works. However, the community of smart home network is vulnerable to energy theft. Such attackscannotbeeffectivelydetectedsincetheexistingtechniques require certain devices to be installed to work. This imposes a challenge for energy theft detection systems to be implemented despite the lack of energymonitoring devices.Thispaperdevelops an energy detection system called Smart Energy Theft System (SETS) based on machine learning and statistical models. There are 3 stages of decision-making modules, the first stage is the prediction model which uses multi-model forecasting System. This system integrates various machine learning models into a single forecast system for predicting the power consumption. The second stage is the primary decision making model that uses Simple Moving Average (SMA) for filtering abnormally. The third stage is the secondary decision making model that makes the final stage of the decision on energy theft. The simulation results demonstrate that the proposed system can successfully detect 99.96% accuracy that enhances the security of the IoT basedsmarthome.

Index Terms—Smart homes, Smart grid, Internet of things, Energy theft, Machine learningtechniques

I. INTRODUCTION

In the modern smart grid, massive deployment of advanced metering infrastructures (AMI) facilitate the efficient and reliable information exchange. The AMI can be divided into different sectors depending on the location which is crucial to end consumer. AMI includes smart meters and Internet of Things (IoT) monitoring devices that were able to collect data inlargevolumesandfastspeed.

Smart home innovators today focus on system development, system architecture, communication protocols, and forecasting tools [1], [2]. These innovations provide home consumers with a better technology in terms of energy monitoring, control, and reliability. For example, Demand Side Management System (DSMS) was introduced to better manage and control power consumption for the smart homes [3]. This power conservation concept increased the research on improving DSMS methods like load-shifting, dynamic price management, forecasting demand, and demand response systems [4]–[6].

These advancements improved through the use of machine learning and statistical modelling. Algorithms such as Simple

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Moving Average (SMA), Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) have been used in the energy efficiency sector [7]–[10]. However, it is still vulnerabletomaliciousbehavioursuchasenergytheft.

Energy theft has been a rising issue for various countries around the world. Despite this, only a few preventive energy theft methods were created to combat the issue. Zhou, Y. et al. proposed a dynamic programming algorithm for leveraging probabilistic detection of energy theft in the smart home [11]. This proposed method requires the deployment of Feeder Remote Terminal Unit (FRTU) on top of a smart meter which incurs high costs for consumers. Additionally, it works only undertheassumptionthatasmartmeterisavailable.

Liu,Y. and Hu, S. proposed a detectiontechniquethathasa detection accuracy of 92.55%onaverage[12].Thisproposeddetectiontechniqueintegrated Bollinger-bands-baseddetectionwiththepartiallyobservableMarkov-decisionprocess(POMDP). However, it does notreflectonall conditionsof a house environment. Firstlythehousedemanddatahasconsistent energy consumptionthroughouttheentire24hours.Itdoes notincludeanyzeroenergyconsumptionfora particularhour.AnotherconditionontheBollinger Bandmethod,thedeviationcanonlybedoneinaconsistentrangeofenergyusage.

However, if the range ofenergyusagebecamelarge,theBollingerBandmethodcouldnotbeusedduetoits deviation.ThispaperproposesanovelideaofSmart EnergyTheftSystem(SETS)forthesmarthome.Thisenergytheftdetectionalgorithmismoreefficientandreliablecomparedtopreviousmethods.Asaresultofanon-intrusivemethodofdatacollection,theenergymonitoring systemwasimplementedin a realhouseinSingapore. The collected dataincludesTimeseriesdatapowerconsumption from anon-controlledreal-life house environment.

The remaining paper is organised as follows: Section II presents background information about the foundation of the Smart Energy Theft System (SETS). Section III shows the proposed methodology for Smart Energy Theft System(SETS). Section IV provides the simulation results of the proposed system.Finally,thepaperisconcludedinsectionV.

II. BACKGROUND INFORMATION

A. SmartHomes

SmartHomesarecreatedthroughimplementationofInternet of Things (IoT) and smart meters [13]–[16]. In order to monitor and control the Advanced MeteringInfrastructure (AMI), Energy Management System (EMS) was an essential integration of the system infrastructure [17]–[20].

Demand Side Management System (DSMS) is included as a function of EMS [21]. Its functionality focuses mainly on managing the demand response and loads. It collects the demand information to dictate the optimal power usage such as implementing load-shifting to enable the use of electricity marketsduringpeakandoff-peakhours.

It allows users to conveniently dictate their smart appliances within the home area by using mobile devices. More advanced and developed systems could further analyse the data collected and make its own decision for the smart homes to operate in a cost-effective and energy-efficient method based on users' consumptionpatterns.

B. EnergyTheft

Energy theft has become a serious issue in the smart grid community [22]. It has caused massive losses for many countries that exceed billions of dollar. Nowadays, a smart meter will be placed at the end of every distribution network to record power consumption and generates the energy reports remotely. An example of the home distribution network is shown inFig.1.

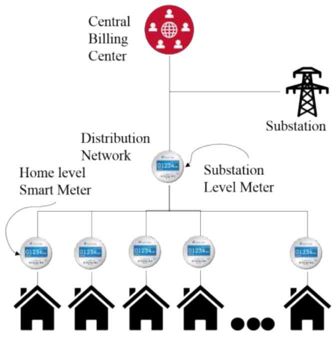
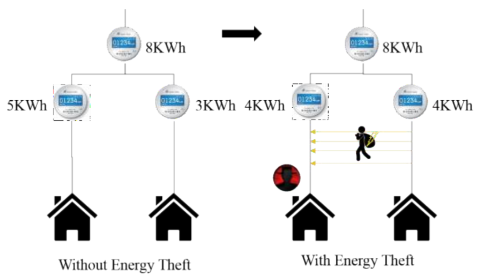


Fig. 1: Home distribution network

Energy theft methods involve hacking smart homeappliance and most commonly direct hooking on other households electricity supplies. Other methods involved are tampering with the smart meter's software, mechanism, andmanipulating data through cloud storage [23]. Thus, attackers can reduce their own electricity usage by manipulating other households through tampering and hacking to increase their electricity usage as the aggregate bill for all customers in the community remains the same [24]. Fig.2 shows an example of energy theft situation.



The example shows that through energy theft, the higher consumption household can reduce their own power consump- tion through tapping on another household. It increases the electricity bills for the other household victim while reducing the energy theft culpritbills.

III. PROPOSED SMART ENERGY THEFT SYSTEM(SETS)

Fig.3showstheoveralldesignoftheproposedSmart Energy

Theft System (SETS) for the smart homes. SETS is designed fordetectingenergytheftandalertingtheconsumer s.Itcollects information from monitoring devices and analyses the data to detect energytheft.

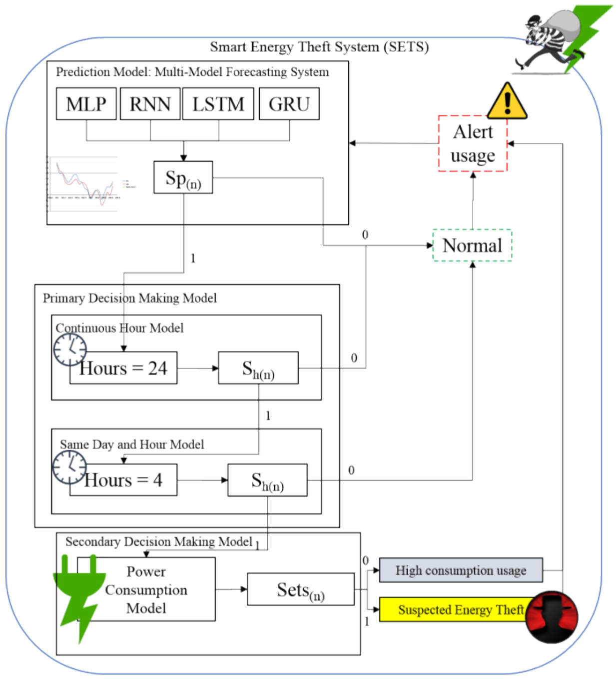


Fig. 3: Overall SETS architecture

The overall architecture comprises the following modules:

- DataCollectionModule
- PredictionModel
- Primary DecisionMakingModel
– ContinuousHourModel
– Same Day andHourModel
- Secondary DecisionMakingModel
– Power ConsumptionModel

The data collection module collects the data for SETS. The first stage of SETS is the prediction model. The prediction model uses Multi-Model Forecasting System that comprises different machine learning methods: Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory(LSTM),andGatedRecurrentUnit(GRU) .Itpredicts and compares the actual data to detect abnormally. Second stage of SETS is the primary decision making model. This stage uses a statistical model called Simple Moving Average (SMA)tofiltertheabnormallyfromthefirststage.

Third stage of SETS is the secondary decision making model. This stage further filter from the second stage and decides whether energy theft had occurred. After taking the final decision, the whole process will be repeated for the next incoming data. SETS is best implemented with an independent hardwaresystemdirectlyatthesmartmeters,thisisbecauseany interferencesforenergytheftregardlessoftamperinghardware or manipulation of data can be detected. It is more accurate compared to just monitoring the data from cloud or operator's databaseasmanyotherfactorsmayaffecttheanalysis.

A. Data CollectionModule

Demand Side Management System (DSMS) collates the information from various real-time monitoring smart devices in the house. The data collection module for setting up Smart Energy Theft System (SETS) is to get the real-time monitoring ready. Data collection module used a set of smart plugs called Aeon Labs Z-Wave UK Plug-in Switch plus Power Meter and the main controller was a VeraEdge Home Controller. ConnectivityfordatacollectionisshowninFig.4.

Fig. 4: Data collection system architecture

This system was placed on a Singapore smart home for collecting data through a non-invasive method of energy monitoring.

B. SETS

SETS detects unexpected energy theft from any form of malicious attack. This proposed system is designed with the following stages:

1) Stage 1: Prediction model: Multi-Model Forecasting System: The Prediction Model forecast the next 24 hours by using Multi-Model Forecasting System. Measured data is used for predictions and comparison to determine the energy theftsituation.

a) Stage 1: Multi-Model Forecasting Systems and Algo- rithms: The Multi-Model Forecasting System uses different machine learning methods and utilises the most accuratemodel throughthestateofpredictionmodeldecisionmakingconditionsp(n). The forecasting systems Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) are used at this stageandabriefdescriptionisasfollows:

- Multi-layer perceptron(MLP)

Artificial neural networks (ANN) are often called neural networksormulti-layerperceptron(MLP)torepresentthe most useful type of neural network. It is inspired by the biological architecture of the brain which can be used to solvedifficultcomputationaltasks.Thegoalisdeveloping robust algorithms and data structures that can be used to solve difficult problems [25].

:Hiddenlayeroutput,Wnk:Input-to-hiddenlayerweights, βnk: Hidden-to-output layer weights, and σ : Activation function.

By using the hidden layer function, the best set of results canbefoundinthenetwork.ThepowerofMLPprediction capability comes from the ability to learn from training data and relating the best testing data to the given output data in a hierarchical or multi-layered structure of the network. It uses supervised learning technique called backpropagation for training the network. Due to its popular ability to solve difficult problems, a variety of MLP was created to optimise the result for different types ofissue.

- Recurrent NeuralNetwork(RNN)

RNNs are a type of artificial neural network that was designed to learn patterns in data sequences such as numerical time series data, images, and text. It is a powerful type of neural network that has been used in industries such as sensors, the stock market, and governmentagencies.

Fig.6showstheRNNfullnetwork(unfolded)whichisthe completesequenceofthenetwork.Forexample,ifthereis a sequence of three numerical values, the network would unfold into a three-layer neural network that supports a layer for eachnumericalvalue.

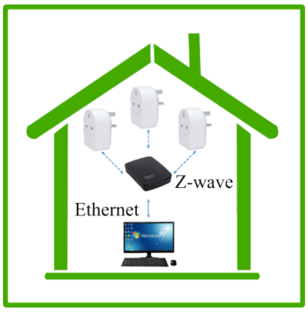


Fig. 6: Recurrent neural network and

unfolding sequence diagram

The computational formulas [27] in an RNN happens as follows:

$s_t = \sigma(s_{t-1}.W + x_t.U + b)$ (3)

$o_t = s_t.V$ (4)

Where,t:Timestep,xt:Inputdata,ot:Predictedoutput,

st: Hidden state, U : Input-to-hidden weights,W :Hidden-to-hiddenweights,V:Hidden-to-outputweights,

b : Bias value, and σ : Activation function.

Hidden state stis considered the memory of the network; it captures information about the situation in all previous time steps which was the main feature of an RNN. otis the output predicted solely based on the current memory at time step t. RNN weights U , V , W are constant throughout the process, unlike traditional neural network whereitisdifferentateachlayer.Thisreducesthenumber ofparametersrequiredtobelearntbyperformingthesame taskateachtimestepbutwithdifferentinputs.

• Long Short TermMemory(LSTM)

One of the appeals of RNNs is the idea that they might be able to connect previous information to the present task. In cases where the gap between the relevant information and the place which is required was small, RNNs is able to learn and utilise the past information [28]. However, if the gap is huge, RNN is unable to link the information forthelearningprocesstokickin.

In order to solve long-term dependency issues, a special kind of RNN called Long Short Term Memory (LSTM) networks were created. It was introduced by Hochreiter& Schmidhuber[29]whichwasthenpopularisedandrefined bymanypeopleinvariousindustriesasitworksextremely well on a variety of problems. Fig. 7 shows how each blockofLSTMnetworkinteractswitheachother.

Fig. 7: LSTM network diagram

Fig.8 shows the details of the LSTM block [28]. In Fig. 8, each line carries an entire vector, from the output of one node to the inputs of the others. The grey circles represent pointwise operations, similar to vector addition, while the orange boxes are learned neural network layers. Lines (vector transfer) denote content going to different locations.

Fig. 8: LSTM block diagram

The computational formulas [30], [31] in an LSTM block are defined as follows:

$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$ (5)

$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i)$ (6)

$\acute{\c{C}}_t = \tanh(W_c.[h_{t-1}, x_t] + b_c)$ (7)

$C_t = f_t.C_{t-1} + i_t.\acute{\c{C}}_t$

(8) $o_t = \sigma($

$W_o.[h_{t-1}, x_t] + b_o)$

(9) $h_t = o_t$

$.\tanh(C_t)$ (10)

Where, t : Time step, xt: Input value, ht: Output value, ot: Output gate, ft: Forget gate, it: Input gate, Ct: Cell state,C´¸t:Candidatevalue,Wo:Outputgateweights, Wi:Inputgateweights,Wf:Forgetgateweights,Wc :

Cell state weights, bo: Output gate bias value, bi: Input gatebiasvalue,bf:Forgetgatebiasvalue,bc:Cellstate bias value, and σ : Gate state.

There are three gates in the block that manage the block state and output:

– Forget Gate ft: decides the information to throwin theblock.

– Input Gate it: decides which input values to

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update thememorystate.

– Output Gate ot: decides the output dependingonthe 238

[32].ThisallowsthecreationoflargeLSTMtoaddress–Thenumberofhiddenlayer[33]:

complex sequence problems and achieve optimal results.

• Gated RecurrentUnit(GRU)

nh=(ni+no)+

√ nt (15)

A variation of the LSTM is the Gated Recurrent Unit (GRU) which was introduced by Cho, et al. [30]. This system has a single update gate which combines the input and output gate. It also merges the hidden and cell state which makes a simplified model than a standard LSTM

Where,nh:Numberofthehiddenlayer,ni:Number of the input layer, n0: Number of the output layer, andnt:Numberofthetrainingsets.

– The Mean Absolute Percentage Error (MAPE):

model. Fig. 9 shows the details of the GRU model [28].

MAPE =

100ΣnA|−iF

i|,whereA 0

n n i=1 Ai

i

(16)

Where, n : Number of data, Ai: Actual output data, and Fi: Forecast output data.

– The Absolute Percentage Error (APE):

APE

= 100(An − Fn),where A

0 (17)

n | n

n

where APEn= Absolute Percentage Error for n.

– The state of prediction:

.

sp(n)

= 0, ifAPEn≤MAPEn

1, otherwise

(18)

Fig. 9: GRU block diagram

The GRU layer is derived from the LSTM layer which results in similar equations:

Where, sp(n): State of prediction model decision making condition.

b) Stage 1: Procedures: The following steps aretaken forthisstage:

•

Step1:Pre-processthedatatoaccumulativedata.

•

Step2:Usingpredictionmodeltopredictthedata.

z =σ(W.[h,x]) (11)

•Step3:UsingMeanAbsolutePercentageError(MAPE)

t z t−1 t to dictate the best predictionmodel.

• Step 4: Use the updated MAPE to comparewithAbsolute

rt=σ(Wr.[ht−1,xt]) (12)

ht=tanh(W.[rt.ht−1,xt]) (13)

Percentage Error (APE) for every hour.

• Step 5: If sp(n)= 1 then go to the next stage, otherwise go to thenextiteration.

2)

Stage2:PrimaryDecisionMakingModel:Thisst age

ht=(1−zt).ht−1+zt.htˇ

(14)

uses Simple Moving Average (SMA) to determine the energy theftpredictions.

Where,t:Timestep,xt:Inputvalue,ht:Outputvalue, rt: Reset gate, zt: Update gate, ht: Candidatevalue, Wr: Reset gate weights, Wz: Updˇate gate weights, W:

a) Stage 2: Algorithms: The following formulas are used forthisstage:

- The Simple MovingAverage(SMA):

Candidate gate weights, and σ : Gate state.

The reset gate determines the new input and previous memory combination and the update gate determines the

1
SMA(n) = n

Σn
xi
i=1

(19)

amount of previous memory to be kept. The idea of using a gating mechanism is similar to LSTM with an objective to learn long-term dependencies. The key differencesare:

– GRU has two gates while LSTMhasthree.

– GRU does not have output gate andinternalmemory.

– GRU trains faster due to lesser parameters.

GRU and LSTM models had solved the long term dependencies issues but the trade-off of both system are not fully explored [32].

Where, n: The number of hours for SMA and x: The variable for the hour in the list.

- The Maximum SMAdifferencealgorithm:

SMA(md)= max f(|SMA(i)−SMA(i−1)|),
i∈n

wheren 0

Where, SMA(md): Maximum of the SMA difference between before andafter.

- Thestate.ofhours:

(20)

- State of Prediction Model(sp(n)) The State ofPrediction

0,if(SMA −SMA)≤3SMA ,

Model (sp(n)) determines the abnormally for energy theft in stage 1. The following formulas were used for this stage:

sh(n)= n
1, otherwise

n−1 4 (md)

(21)

Where, sh(n): State of hours algorithm decision making condition.

b) Stage 2: Procedures: The following steps are taken forthisstage:

- Stage 2.1: ContinuousHourModel:

– Step 1: Calculate Simple Moving Average (SMA) using 24hoursperiod.

– Step 2: Find the difference between the SMA calcu- lation for the last hour and the current hour after 25 hours ofmeasureddata.

– Step 3: Use the Maximum SMA differencealgorithm andproceedtothestateofhoursalgorithm.

– Step4:Ifsh(n)=1thenstarttheSameDayand Hour Model, otherwise go to the next iteration.

- Stage2.2:SameDayandHourModel:

– Step 1: Rearrange the data according to the day and hour.

– Step 2: Calculate SMA using 4 hours of data from thesamedayandhourfromdifferentdates.

– Step 3: Find the difference between the SMA calcu- lation for the last point and the current point after 5 points ofmeasureddata.

– Step 4: Use the Maximum SMA differencealgorithm andproceedtothestateofhoursalgorithm.

– Step 5: If sh(n)= 1 then go to the nextstage, otherwise go to the next iteration.

3) Stage 3: Secondary Decision Making model: This stage uses the user's history to find the occasional maximum power usages.

a) Stage 3: Algorithms: The following formulasareused for this stage:

• TheMaximumwattage:

IV. SIMULATION STUDIESAND RESULTS

A. Experiment Setup and DataCollection

TheAeonLabsZ-WaveUKPlug-inSwitchplusPowerMeter were installed on every available energy consumption devices intheexperimentalhouse.Then,thedatawascollectedthrough a centralised smart device called VeraEdge Home Controller. Fig.10showsthedemanddatacollectedfromtheexperimental house. The data collected from 04/12/2016 – 02/04/2017 were inkilowatt(kW)andtimestamp(DD/MM/YYYY HH:MM).

Fig. 10: Plot of experimental house demand data

B. SmartEnergyTheftSystem(SETS)Results

The SETS was tested using simulated energy theftscenarios. The scenario was created by randomly stealing energy on 50 different periods. Fig.11, 12, 13, and 14 show the respective predictionresultsforMLP,RNN,LSTM,andGRU.

P(md)=maxf(P(|i)) |
i∈n

(22)

Where, P(md): The maximum power from the list of measurement.

• The state ofenergytheft:

.

sets(n)=

0,if3P(m4d)≤Pn≤P(md)
1, otherwise

(23)

Where, sets(n): State of energy theft algorithm decision making condition.

b) Stage 3: Procedures: The following steps aretaken forthisstage:

• Step 1: Find the Maximum watt and proceed to thestate of energytheftalgorithm.

•

Step2:Ifsets(n)=1thenpossibleenergytheft,otherwise unexpectedhighconsumptionusagefromconsumers.

• Step3:Proceedtonextiteration.

After all the stages are completed, it will move to the next period and repeat the process from stage 1. However, SETS requires at least 5 weeks of non-malicious data collection at every hour in order for the system to learn from the historical data. This learning will be constantly updated for real-time monitoring and it can increase its accuracy with more data coming in.

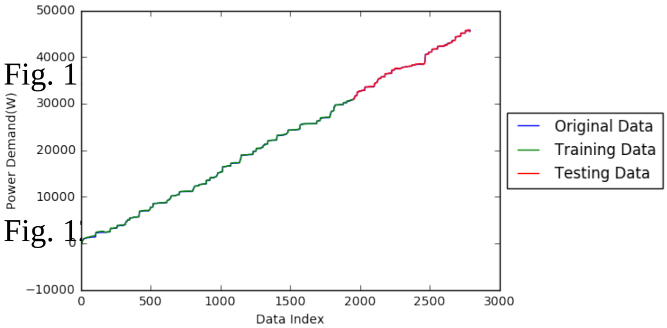

Fig. 1

Fig. 1

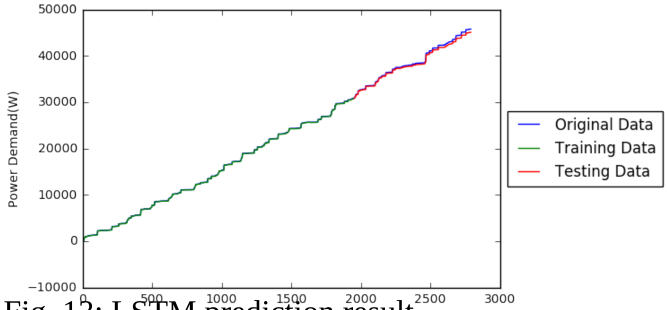

Fig. 13: LSTM prediction result

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Fig. 14: GRU prediction result

Table I shows the MAPE results for different forecasting systems. The best MAPE result was 0.18% which was consideredmostsuitablemethodascomparedtoothermethods tested.

TABLE I: SETS: Prediction model MAPE results

Prediction model MLP RNN LSTM GRU
MAPE(%)-Train 33.99 2353.235.48 11.20
MAPE(%)-Test 0.18 68.83 0.81 1.32

Fig.15 shows the stage 2 alert system for Smart Energy Theft System (SETS). These results were obtained after the dataprocessedthroughstage2inSETS.

Fig. 15: SETS: Stage 2 alert notifications

Prediction model	MLP	RNN	LSTM	GRU
MAPE(%)-Train	33.99	2353.23	5.48	11.20
MAPE(%)-Test	0.18	68.83	0.81	1.32

In Fig.15, the alert notifications were made after processing through stage 2. It filters the abnormally from stage 1 and proceeded to stage 3 if it is not able to make a decision.

Fig.16 shows the stage 3 final stage alert system for Smart EnergyTheftSystem(SETS).Theseresultswereobtainedafter thedataprocessedthroughstage2and3inSETS.

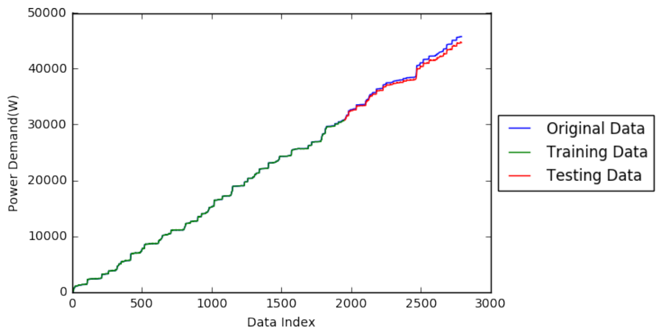
```
Possible Sudden High consumption usage:'4/1/2017 13:00'
Possible Sudden High consumption usage:'1/3/2017 21:00'
Possible Energy Theft:'29/3/2017 21:00'
Possible Sudden High consumption usage:'12/1/2017 13:00'
Possible Sudden High consumption usage:'2/2/2017 15:00'
```

Fig. 16: SETS: Stage 3 alert notifications

In Fig.16, the final stage alert notifications were made from filtering stage 2 and using stage 3 algorithms. This results in 99.96% accuracy of classifications using SETS with all stages implemented.

C. Discussion

Table II shows classification results for different cases with



thesameenergytheftscenario.ThecasesinTableIIweredone by randomly stealing the energy of 50 different periods. These conditions were maintained to present a fair environment for the detection capability of Smart Energy Theft System(SETS).

TABLEII:Summaryofclassificationresultsindifferentstages

SETS Case Studies	Classification Accuracy (%)
Case 1: Stage 1	56.39
Case 2: Stage 2	99.46
Case 3: Stage 3	0.68
Case 4: Stage 1 & 3	56.87
Case 5: Stage 2 & 3	99.89
Case 6: Stage 1 & 2	99.89
Case 7: All Stages	99.96

SETS Case Studies Classification Accuracy (%)
Case 1: Stage 1 56.39
Case 2: Stage 2 99.46
Case 3: Stage 3 0.68
Case 4: Stage 1 & 3 56.87
Case 5: Stage 2 & 3 99.89
Case 6: Stage 1 & 2 99.89
Case 7: All Stages 99.96

Table III shows classification results for different sub-cases with the same energy theft scenario.

TABLE III: Summary of classification results for sub-cases

SETS Sub-Case Studies	Classification Accuracy (%)
Sub-Case 1: Stage 2.1	2.04
Sub-Case 2: Stage 2.2	19.39
Sub-Case 3: Stage 2.1 & 3	99.39
Sub-Case 4: Stage 2.2 & 3	99.32
Sub-Case 5: Stage 1 & 2.1	99.4
Sub-Case 6: Stage 1 & 2.2	99.4

SETS Sub-Case Studies Classification Accuracy (%)
Sub-Case 1: Stage 2.1 2.04
Sub-Case 2: Stage 2.2 19.39

Sub-Case 3: Stage 2.1 & 3 99.39
Sub-Case 4: Stage 2.2 & 3 99.32
Sub-Case 5: Stage 1 & 2.1 99.4
Sub-Case 6: Stage 1 & 2.2 99.4

Case 1, 2, and 3 were a single stage detection system. Case 4, 5, and 6 were 2 stages detection systems. Case 7 represents the Smart Energy Theft System (SETS).

Case1,2,and3achievedclassificationsaccuracy of56.39%, 99.46%,and0.68%.Amongthesinglestagedetectionsystems, case 3 had the worst accuracy result while case 2 had the best accuracy results. However for case 2, further findings were found by separating stage 2 into stage 2.1 (Continuous Model) and stage 2.2 (Same Day and Hour Model). Sub-cases 1 and 2 achieved just 2.04% and 19.39% respectively. Case 2 had further demonstrated that by integrating the 2 models, it shows tremendous improvements fordetectiontechniques.

Case4,5,and6achievedclassificationsaccuracy of56.87%, 99.89%, and 99.89%. Among the 2 stages detection systems, case 4 had the worst accuracy result while case 5 and 6 had the best accuracy results. 2 stages integration results show improvements compared to single stage detection systems. Case 5 was further analysed in sub-case 3 and 4. Sub-case 3 had a 99.39% accuracy and sub-case 4 achieved99.32%.Case

6 was also further analysed in sub-case 5 and 6. Sub-cases 5 and 6 had both achieved 99.4%. Case 7 was done using SETS to achieve a classification accuracy of 99.96%.

After reviewing all the cases, it shows significant increment by integrating the different stages in SETS. By using a single detection system, detection accuracy results like Case 1 and 3 would not be efficient enough for energy theft situations. By integrating 2 detection systems, although case 4 was still not efficient but case 5 and 6 had shown considerable improvements on its classification accuracy. Ultimately, this led to an integration of all 3 detection techniques with the best classification accuracy amongallcases.

V. CONCLUSIONS

In this paper, an innovative Smart Energy Theft System (SETS) is proposed for energy theft detection. A Multi-Model Forecasting System based on the integration of machine learning models such as Multi-Layer Perceptron (MLP), Re- current Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) was developed as part of SETS. Additionally, a statistical model called Simple Moving Average (SMA) was also further developed intoSETS. These algorithms enable SETS to efficiently detect energy theft activities. The evaluation of its system carried out in a Singapore home environment. Stage 1 has an energy theft accuracy result of 56.39%, by adding stage 2 has 99.89% and all 3 stages present the evidence of its energy detection algorithm accuracy of 99.96%. In conclusion, SETS enhances the security of the Internet of Things (IoT) based smart home systems from energy theft and can be further implemented in commercial and industrialsectors.

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