LSTM and GRU

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Long Short Term Memory and Gated Recurrent Unit Predictive Models for Industrial Control Systems

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ABSTRACT

As Operational Technologies (OT) and Internet of Things (IoT) grew popular, Industrial Control Systems (ICS) which are frequently managed through a Supervisory Control and Data Acquisition (SCADA) systems gained importance but simultaneously anomalies in ICS became a security concern. This paper presents a data-driven approach of predictive modeling for Energy Management System logs that exploits the relationship between data elements in the logs and the predictable aspect of communication patterns between devices in ICS networks using the time series structure of their logs. Specifically, two Recurrent Neural Networks - Stacked Long Short Term Memory (LSTM) and Stacked Gated Recurrent Unit (GRU) models - are employed for modeling the behavior of these logs and comparison between these models is demonstrated. Various measures like accuracy, loss, memory usage and testing time are utilized to check and compare the performance of the models.

Keywords: Industrial Control System; Energy Management System; Data-driven Modeling; Deep Learning; Recurrent Neural Network; Long Short Term Memory; Gated Recurrent Unit.

2012 Computing Classification System:

- **Security and privacy~Intrusion/anomaly detection and malware mitigation~Intrusion detection systems**
- **Computing methodologies~Modeling and simulation~Model development and analysis**
- **Computing methodologies~Machine learning~Machine learning approaches~Neural networks**

1 Introduction

Digital transformation connects Operational Technology like never before. That connectivity makes industrial organizations smarter and safer, gives them better management, greater visibility and improves uptime and productivity. But modern plans have a high degree of interconnectivity which opens the Operational Technology (OT) environment to outside threats. Reference(Allhoff and Henschke, 2018) discusses ethical issues related to IoT. An OT cyberattack affects more than just data. It can cause physical harm to personnel, environment and industrial equipment, and thus, disrupt productivity. OT professionals are at a disadvantage because they are at the beginning of the security journey. To safeguard their environment, they need a total security program that helps them understand the risks, improve asset visibility across the organization and remedy the impact of cyberattacks(Murray et al., 2017).

Energy production, large scale manufacturing and all forms of automated processing have become critically dependent on digital communications and computer networking abilities. Information Technology is appearing throughout the operational space by the way of devices like smart meters, automated asset distribution systems and self-monitoring transformers, because of increasing wired and wireless communication between the growing number of smart devices. Modernization of OT through IT integration brings with it the required consideration of security. OT/IT convergence empowers more target control and monitoring with an easier investigation of data from network systems anywhere in the world.

Industrial Control Systems (ICS) which are an indispensable element of OT, are made up of the machines, systems, networks, and controls used to manage and automate industrial activities, improving their efficiency and lowering their cost (Kargl et al., 2014). ICS functions vary according to the industry where they are applied. It is an umbrella term consisting of Distributed Control System (DCS), confined to a single location, like a certain factory, as well as, SCADA, used for systems that are scattered over a considerable topographical region, like a power grid. Its components - Programmable Logic Unit (PLC), fieldbus, human machine interface (HMI), workstation, etc - are explained in brief in (Chapman et al., 2016). It also provides an analysis of several security measures for ICS. Reference(Stouffer et al., 2015) also summarizes the security mechanisms present in such systems.

Supervisory Control And Data Acquisition system (SCADA) gathers information from devices and sensors positioned at a remote location in the field and transmits it to the main station. The collected data are observed and analyzed on the SCADA connected computers in the main station. Based on this analysis, commands given by the computer or the operator can be relayed to control devices present at a substation in the field, also known as field devices. SCADA systems generally function with little human intervention and provide real-time environment supervision. This is possible because of the periodic acquisition of data like meter readings, sensor status, etc. Reference(K.Sayed and H.A.Gabbar, 2017) elaborates this well. A real-time knowledge generation component is designed in (Skripcak and Tanuska, 2013) to store and process these continuous values.

One such avenue where SCADA can be adopted for system optimization is *Energy Management Systems (EMS)*. With the development of technology, electrical energy has emerged as an essential for the socio-economic growth of society. SCADA monitoring helps in increasing the energy efficiency of EMS. Such a SCADA-enabled EMS is described in (Mesaric and Palasek, 2014), which demonstrates the architecture for incorporation of the sophisticated networking technologies with the conventional SCADA software. Renewable Energy Management System along with its structure and implementation using SCADA technology is illustrated in (Dumitru and Gligor, 2012). Much research is going on in enhancing EMS that employs SCADA and making them smarter. A novel framework for an intelligent dynamic energy management system that combines dynamic programming and reinforcement learning is introduced in (Venayagamoorthy et al., 2016). Reference (Ashok et al., 2014) suggests a game-theory approach to deal with coordinated cyberattacks in smart-grids.

Data-Driven Modeling (DDM) relies on the analysis of the data gathered from the system. A model is designed based on relationship between the state variables of the system(input and output) by making some assumptions about its physical behaviour. This approach has potential to advance much more than the conventional empirical one. It facilitates numerical predictions, reconstruction of highly nonlinear functions, data grouping, classification, etc. Many such applications in various scientific disciplines are elaborated in (Montáns et al., 2019)

Deep Neural Networks (DNN) spearheads the data-driven methods and can be utilized for refining the EMS. The multiple layers in deep learning provide multi-level abstraction and help in identifying relationships between input and output as well as in discovering intricate patterns in large data sets. An analysis of this is found in (LeCun et al., 2015). One application of DNN in EMS is for Energy Load Forecasting. Reference(Amarasinghe et al., 2017) investigates the effectiveness of using various DNN models - Convolutional Neural Network (CNN), LSTM, Support Vector Machine (SVM), etc - for forecasting energy load. Another paper that explores the application of deep neural networks in renewable energy systems for energy forecasting is (Wang et al., 2019). A DNN architecture employing stacked auto-encoder (SAE) and stacked denoising auto-encoder (SDAE) has been projected in (Khodayar et al., 2017) for ultra-short-term as well as short-term forecasting of wind speed, which shows that DNN outperforms ANN with shallow architecture and models complicated non-linear relationships.

Recurrent Neural Networks (RNN) is a class of Deep Neural Networks that accepts time-series as input and hence has vast applications in sequential data. An implementation of RNN and its subclasses on event logs is explained in (Hinkka et al., 2019). The paper illustrates predictive modeling as the event logs are input to predict the next event as output. Methods for attribute clustering and selection to create features are also explained. An RNN model, trained on previously recorded data, is applied to obtain the impedances of a dc power electronic system in (Xiao et al., 2010). These impedance characteristics can be utilized in stability analysis of the power-electronics-based distributed power systems. Reference(Teixeira et al., 2011) explores

the security of SCADA-enabled EMS from intelligent attacks. An LSTM model for intrusion detection is illustrated in (Gao et al., 2019) for SCADA systems. Reference (Shi et al., 2018) introduces an RNN model with a new evaluation index and the dragonfly algorithm for tuning. This model is used for interval forecasting in wind power systems, to compute the uncertainties in energy production.

Anomaly detection is the identification of data points, observations or events that do not conform to the regular pattern present in the logs. It is also helpful in behavior analysis. A hybrid approach of detecting anomalies by applying multi-start metaheuristic techniques and genetic algorithms is elaborated in (Ghanem et al., 2015). In that paper,a number of detector having high anomaly detection accuracy were generated for large datasets and then detector reduction stage was invoked. Anomaly and attack detection models for IoT sensors have been implemented in (Hasan et al., 2019) applying various Machine Learning approaches. In another method proposed in (Trnka et al., 2020), to keep the IoT appliances secure, The Network Context is employed by performing multiweek case study on a network with a large number of active appliances. Reference(Hollingsworth et al., 2018) inspects various DNN models for anomaly detection. An approach for automated error detection and isolation in computer-based manufacturing systems based on Deep Auto-Encoders (DAEs) is elaborated in (Iqbal et al., 2019).

Modern RNN-based learning technologies are implemented to generate knowledge about abnormality that happened in the system by predicting the next event. This neural network-based approach is considered as one of the core parts of modern industrial information and control system. Reference(Nguyen et al., 2018) shows such a neural network used for anomaly detection or prediction. LSTM model is applied for this network. The anomaly detection system implemented in (Feng et al., 2017) applies an interesting approach of using a multi-level system in which the first level identifies package content signatures and compares them to those stored in a database using Bloom filter. The second level applies stacked LSTM for predictive modeling on data to predict the next package signature.

The major contributions of this paper are:

- An effort to make ICS secure by generating data-driven predictive models for anomaly detection.
- Deep learning techniques, which are regularly favored for security in Information Technology as well as for Data-driven Modeling, are practiced in Operational Technology.
- An approach to anomaly detection that takes advantage of the predictable pattern in event logs.
- A comparison between LSTM and GRU models over an ICS dataset.

2 Methodology

2.1 Problem Statement

Anomaly detection is employed for identifying malicious activities or events in Industrial Control Systems. It can be enforced using a predictive modeling method. This paper illustrates one such approach where LSTM and GRU are input a sequence of events and the predicted next step is displayed as output. The dataset is the event logs of an Energy Management System where *SCADA category* and *Device type* are taken as features and arranged into time series of 18 events. Two required labels *SCADA category* and *Device type* are output through two separate RNN models. With the help of *SCADA category*, the next event can be known, while *Device type* can be used to track down the device where the event will occur. High priority critical situations can be mitigated with this knowledge. A comparative analysis between LSTM and GRU for this predictive modeling application is demonstrated.

2.2 Dataset

Industrial Control Systems (ICS) cyber attacks dataset was provided on a google site by *uah.edu* (The University of Alabama in Huntsville). The dataset includes 30 days of events as logged by an Energy Management System (EMS) at an investor-owned utility in the United States of America. Data were anonymized by changing the names of operators, devices, and facilities. Events in the data were arranged in rows where each row was a unique event, except the first row which gives names of the columns. Dataset consisted of several attributes like *EventId*, *Event Timestamp*, *SCADA category*, *TOC*, *AOR*, *Priority code*, *Substation*, *Device type*, *Device*, *event message*. Table 1 describes the dataset. The distribution of Events in the dataset according to Priority Code is depicted in Figure 1.

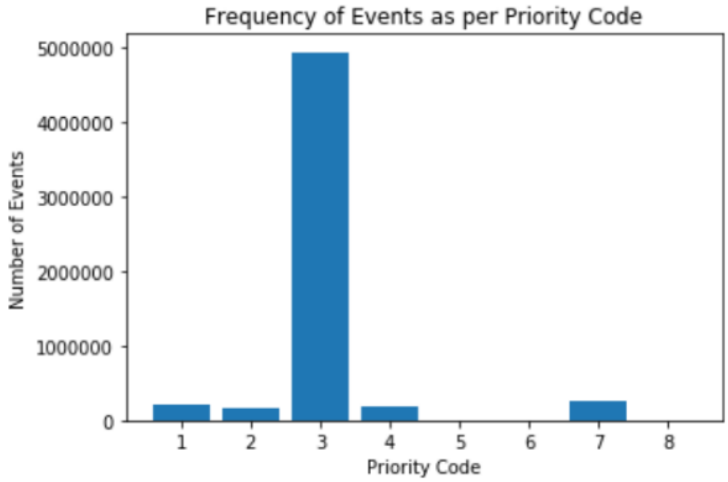


Figure 1: Distribution of Events to Priority Code

Table 1: Dataset description

Attributes	Description
EventId	A numerical value which is a count of events in the file.
Event Timestamp	Date and time of the event. The date is organized as *Year-Month-Day* where year is always 2017, the month is always 05 (May), and the day varies from 1-31.
SCADA category	The type of event being logged.
TOC	Indicates the source system.
AOR	Area of Responsibility, used to define the controlling authority (which operators).
Priority code	Code used to prioritize the events. It ranges from 1 to 8, where 1 is the highest priority and 8 is the lowest
Substation	The name of the substation where the event originated.
Device type	The type of device from which the event originated.
Device	The Device column provides the name of the device which generated the event.
Event message	The event occurring is defined specifically.

2.3 Preprocessing

- *Data Cleaning*
  The data contained inaccuracies and inconsistencies. Hence it was cleansed to remove these inaccurate and inconsistent records and irrelevant columns.

- *Data Reduction*
  Data were analyzed statistically and the attribute subset selection technique was adopted to select highly relevant attributes. *SCADA category* and *Devices* were considered as these highly relevant attributes. But the number of *devices* was too large to be modeled so devices were clustered on the grounds of *Device type*. Smaller clusters of *Devices* having low priority were discarded. Table 2 shows the statistical values and distribution of *Devices* when grouped by *Device type*. This implies that if the device type of the device, where the next event is predicted to occur, is known then there is a 50% (median) probability that the number of devices of that particular device type is less than or equal to 108. It would be much easier to monitor those 108 (approximately) devices to know if the next event occurs there instead of spending more time and processing power to pinpoint the device where the next event occurs directly with help of the model. Hence device type was selected for the preprocessed dataset.

Table 2: Distribution of Devices by Device type

Statistical Measure	Number of Devices
mean	286.727
min	11.000
25%	39.750
median	108.000
75%	244.500
max	2763.000

- *Data Transformation*
  One-hot encoding technique was employed on categorical variables to convert them to integer data. By this method, 47 *SCADA categories* and 44 *Device types* were one-hot encoded. The logs were then grouped into time series of length 18 to form features while the next event was taken as the label.

This preprocessed data was split into training and testing datasets in 3:1 ratio. During each epoch the model was trained over and over again on the training data and it continued to learn about the features of data. In the testing phase, the model was used to evaluate and predict the next events on the reshuffled validation dataset.

2.4 Modeling

2.4.1 Long Short Term Memory (LSTM)

LSTM models are utilized to overcome the vanishing gradient problem that is experienced in Recurrent Neural Network (RNN)(Hochreiter and Schmidhuber, 1997). These networks are upgraded version of RNN that have been implemented for various sequence learning problems due to their scope in learning long-term dependencies (Nguyen et al., 2018). LSTMs are designed for applications where the input is an ordered sequence. In LSTM, the nodes are recurrent but they also have an internal state. The node uses an internal state as a working memory space which means information can be reserved and fetched over many timesteps. The input value, previous output, and the internal state are all used in the node's calculations. The results generated through computations provide an output value and update the current state. LSTM has parameters known as gates that control the flow of information within the node. These gate parameters are weights and biases, which means the behavior of the node depends on the inputs. Gates manipulate current information which is saved to the state and regulates output by the current calculation against saved information. So LSTM network is an exceptional type of RNN qualified for learning long-term dependencies. Figure 2 elaborates the structure of LSTM while its steps are given below:

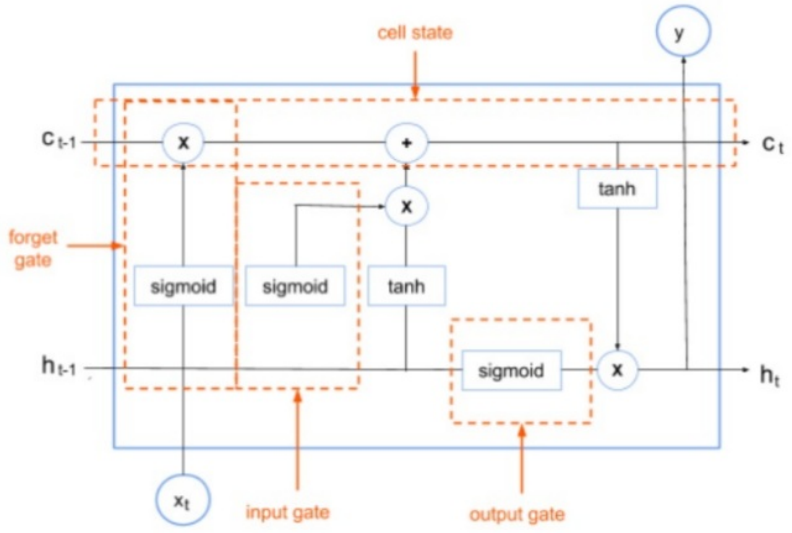


Figure 2: Long Short Term Memory

- A *forget gate* layer identifies the information that is not mandatory and must be discarded from the cell state.

$$f_t = \sigma\left(W_f\left[h_{t-1}, x\right] + b_f\right) \tag{2.1}$$

- An *input gate* layer analyzes and decides the values to be updated. A hyperbolic tangent *(tanh)* layer then formulates candidate values, that would be appended to the cell state. This step determines the new information that will be stored in the cell state.

$$m_t = \sigma\left(W_m\left[h_{t-1}, x_t\right] + b_m\right) \tag{2.2}$$

$$c_{t1} = \tanh\left(W_c\left[h_{t-1}, x_t\right] + b_c\right) \tag{2.3}$$

- In this step, the previous cell state gets updated to the new cell state by forgetting the values which were decided to be unimportant previously and adding new candidate values to each state.

$$c_t = \left(f_t * c_{t-1}\right) + \left(m_t * c_{t1}\right) \tag{2.4}$$

- In the final step, the *sigmoid* layer chooses the measures of the cell state to be declared as output by embedding a cell state through hyperbolic tangent *(tanh)* activation function and multiplying it by the *sigmoid* gate layer output.

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{2.5}$$

$$h_t = o_t * \tanh\left(c_t\right) \tag{2.6}$$

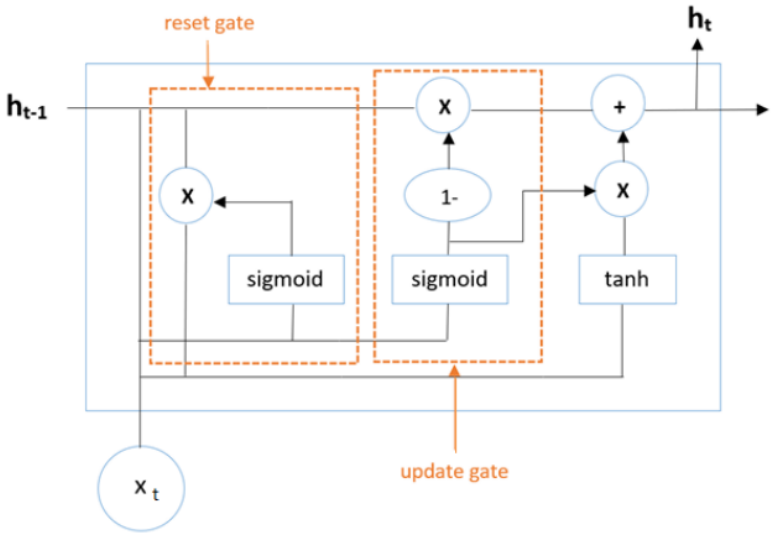


Figure 3: Gated Recurrent Unit

2.4.2 Gated Recurrent Unit (GRU)

It is a simpler version of LSTM. Unlike LSTM, it consists of only three gates and does not maintain an Internal cell state unit. The gating units of GRU regulate the flow of knowledge inside the unit instead of storing it in a separate memory cell(Chung et al., 2014). It merges the input and forget gates into an *update gate*. It also adds a "*reset gate*(Le et al., 2019). Figure 3 explains this structure of GRU and its gates are described below:

- The *update gate* determines the amount of information from previous timesteps that needs to be passed along to the future.

$$z_t = \sigma\left(W_z * x_t + U_z * h_{t-1}\right) \tag{2.7}$$

- The *reset gate* evaluates the amount of the information from previous timesteps to forget.

$$r_t = \sigma\left(W_r * x_t + U_r * h_{t-1}\right) \tag{2.8}$$

- A new memory content will then store the relevant information from the past, with the help of the *reset gate*.

$$h_{t1} = \tanh\left(W * x_t + r_t \odot \left(U * h_{t-1}\right)\right) \tag{2.9}$$

- The *update gate* determines what to aggregate from the current memory content and the previous steps. For holding the current unit information, update gate calculates the output vector.

$$h_t = \left(z_t \odot h_{t-1} + (1 - z_t) \odot h_{t1}\right) \tag{2.10}$$

The weights(W) in both the models represent the strong connection between units and influence the gradient of the activation function and bias (b) is a constant that assists the model to better fit the data.

where h_{t-1} = Output from the previous time step
x_t = Input vector
h_t = Output vector
c_t = Cell state
c_{t1} = New candidate value
z_t = Update gate
r_t = Reset gate
f_t = Forget gate
m_t = Input gate
o_t = Output gate
h_{t1} = Current memory content
σ = Sigmoid function
$\tanh$ = Hyperbolic tangent

2.4.3 Similarities and differences between LSTM and GRU

RNNs undergo vanishing gradient problem, causing hindrance in learn the long data sequences. Both LSTM and GRU overcomes vanishing gradient problems which mainly occurs when parameters and hyperparameters are not set properly(Le et al., 2019). GRU connects forget as well as input gates which is absent in LSTM. GRU uses less training parameters and therefore uses less memory, executes faster and trains faster than LSTM. On the other hand, LSTM is more accurate on datasets using longer sequences. If the sequence is large or accuracy is very critical, LSTM is preferred whereas, for less memory consumption and faster operation, GRU gets priority.

2.4.4 Stacked Predictive Models

In this paper, a stacked approach of executing RNN models is presented for prediction of *SCADA category* and *Device type* of next event. Two LSTM layers with 128 cells each along with an output layer having *softmax* activation are implemented. As the input variables lead to multiclass classification, *categorical cross-entropy* loss function in conjunction with *Adam* optimizer is applied. Two such separate models are produced for the two outputs needed - *SCADA category* and *Device type*. GRU structures are designed in a similar fashion. Figure 4 and Figure 5 demonstrate the architectures of these models.

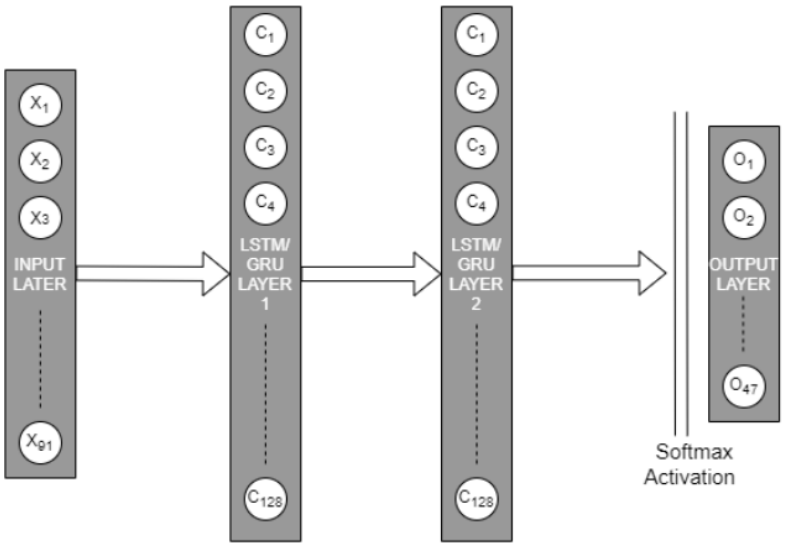


Figure 4: SCADA category predictive model

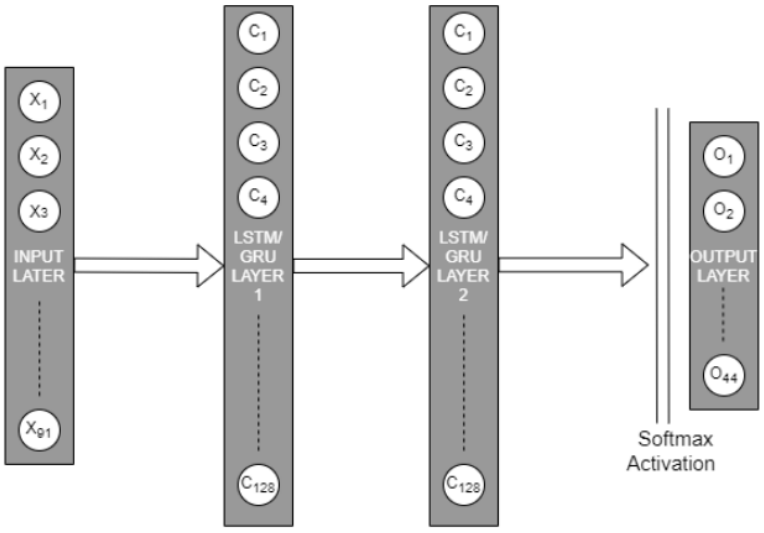


Figure 5: Device type predictive model

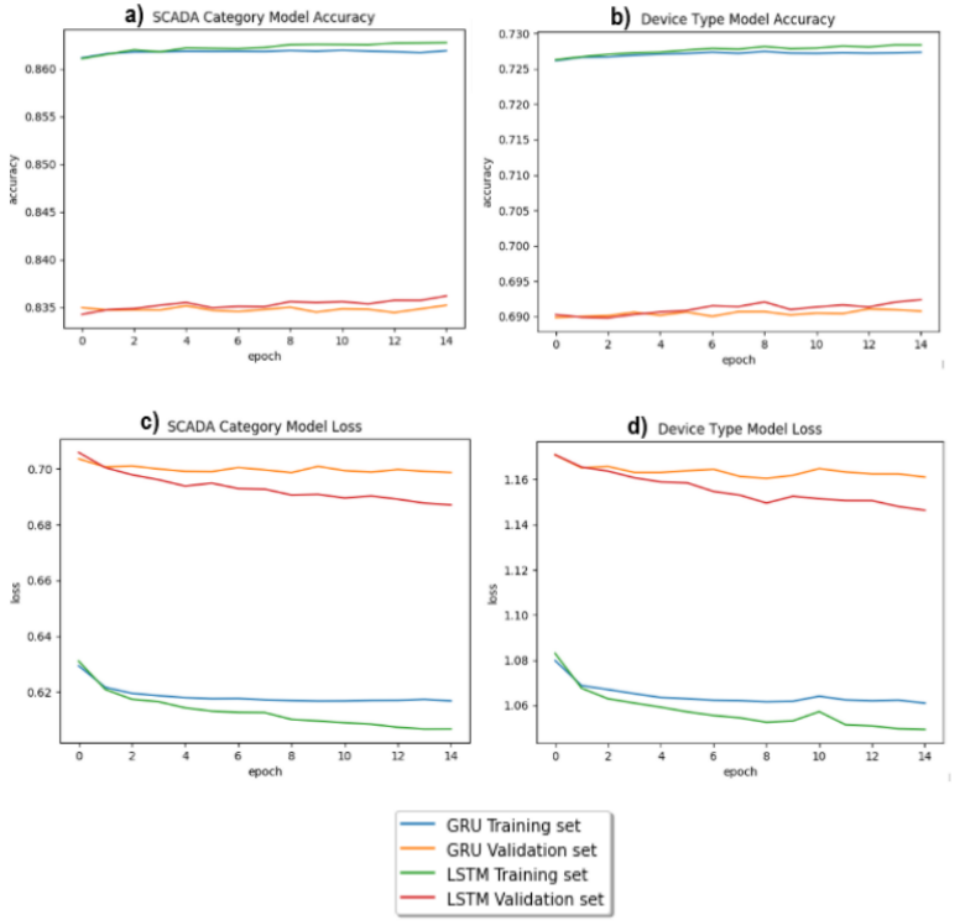


Figure 6: Line graph of (a) SCADA Category Model Accuracy (b) Device Type Model Accuracy (c) SCADA Category Model Loss (d) Device Type Model Loss

3 Results and Discussions

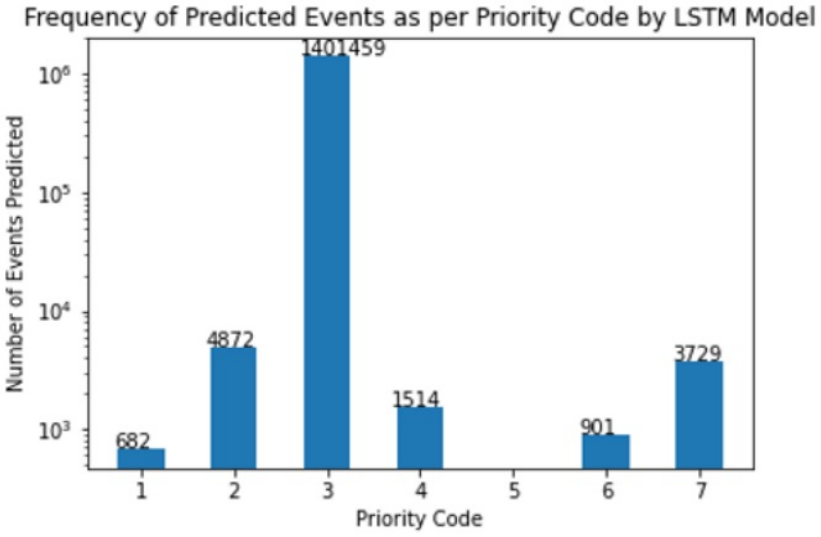
3.1 Training Result

Four models were designed - LSTM for *SCADA category*, GRU for *SCADA category*, LSTM for *Device type* and GRU for *Device type*. They were trained with time series of 18 events, for 15 epochs. This training and validation phase was done on DGX Station on 4 Graphics Processing Units (GPU) and is portrayed below. The accuracies and losses of the 4 models are plotted in Figure 6.

3.2 Model evaluation

Each *SCADA category* has a *Priority code* associated with it. Hence the *Priority code* of the next event can be found from the predicted *SCADA category*. If a high priority event is predicted, the operator can be informed of it. In case the event is anomalous or identified

a)



b)

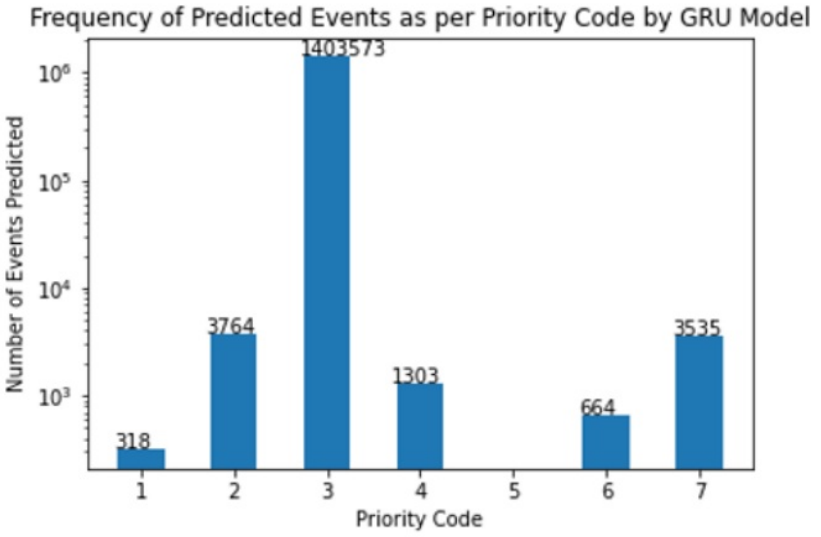


Figure 7: Distribution of Predicted Events to Priority Code in (a)LSTM and (b)GRU Models

Table 3: Comparison between Models

	LSTM-based SCADA category predictive model	**GRU-based SCADA category predictive model**	**LSTM-based Device type predictive model**	**GRU-based Device type predictive model**
Memory	45,56,954 bytes	36,09,296 bytes	45,54,789 bytes	36,06,012 bytes
Testing Time	15 ms/step	13 ms/step	15 ms/step	13 ms/step
Accuracy	0.8129	0.8138	0.6609	0.6620
Loss	0.7624	0.7540	1.2320	1.2208

as a threat, actions can be taken to mitigate it immediately. The plots in Figure 7 denote the distribution of *Priority codes* in the predictions made by the models during testing phase.

3.3 Comparative analysis

During the testing phase, the models were evaluated on a reshuffled validation dataset and compared on the grounds of the result. LSTM gives better accuracy and loss than GRU over the validation phase. On the other hand, GRU marginally outperforms LSTM during testing. Besides that, GRU requires less space and trains faster than LSTM. Further, GRU predicts the results more rapidly, which can be very advantageous for real-time applications. Table 3 consolidates these results of the testing phase.

4 Conclusion

This paper inspects the effectiveness of using stacked LSTM and GRU in designing data-driven predictive models for anomaly detection, on a dataset of Energy Management System logs by exploiting the relationship between data elements in the logs and the time series structure of communication patterns between devices in the network. A comparison between LSTM and GRU models is demonstrated. While the performances of GRU model is comparable to that of LSTM in terms of accuracy and loss, GRU requires significantly less space and is considerably faster than LSTM.

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