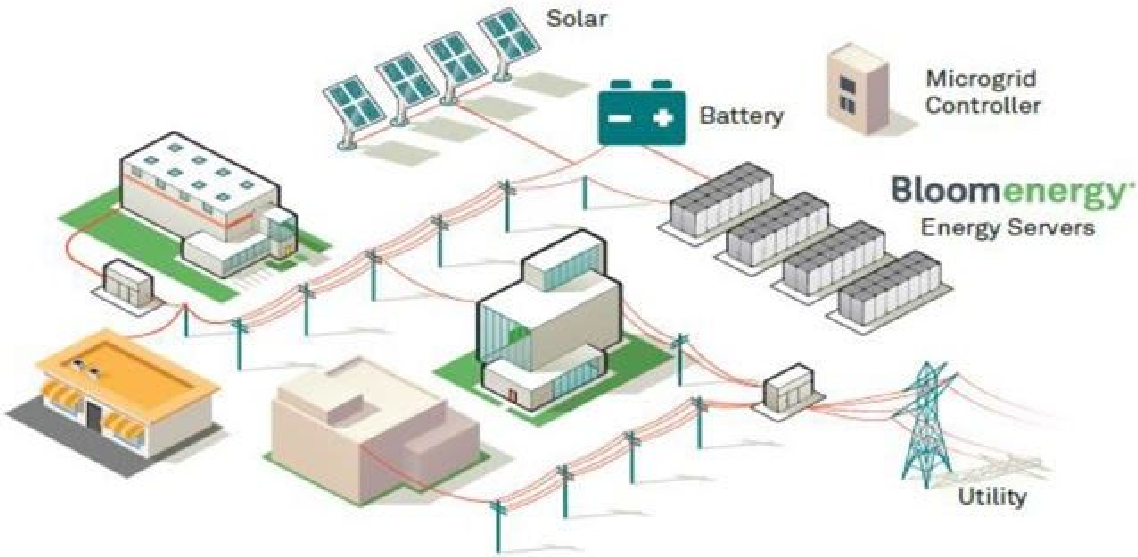
FAULT DETECTION IN POWER MICROGRID



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1. Abstract

This project presents the concept of fault detection and location in a Power Microgrid making use of the machine learning concepts like Artificial Neural Network. The electronic equipment used in microgrids is in essential need of more secure protection against short circuit faults. Due to the high current at the time of fault occurrence, the whole system might be de-energized which would have a severely negative impact on the entire system. A fault occurs when two or more conductors come in contact with each other or ground. Ground faults are considered as one of the main problems in power systems and account for more than 80% of all faults. An effective method to detect, isolate, and protect the power microgrid system against the effects of short circuit faults is extremely important. In this project we worked on a highly effective new method to protect the microgrid system using an Artificial Neural Network (ANN) that will detect and find the location of the fault before it affects other parts of the system. It would, therefore, be more dependable for microgrid protection. This protection network is distributed all along the power microgrid system protecting the entire microgrid network and is connected to the other protective devices in the system.

This project focuses on detecting faults and identifying the location of the faults on electric power transmission lines in the power microgrid network.

2. Introduction

The expansion of renewable energy sources has been a concern in recent years. Even though these conventional energy systems are appropriate substitutions for old power systems, disadvantages and difficulties in power generation and distribution such as overvoltage, fault protection and frequency fluctuations are barriers that should be solved as well.

The future electricity network will need to accommodate large scale of distributed generation units (DGs) and facilitate the connection of grand scale of centralized generation at suitable locations. Microgrid has been considered as an effective way to manage the DGs and other distributed energy resources (DERs) on the distribution system level and the user level. Microgrids provide efficient, low cost and clean energy. These are critical infrastructure that increases reliability and resilience.Also reduce grid “congestion” and peak loads. Still, the protection of these microgrids remains a problematic issue. When a fault occurs in the system, it creates a huge current that could affect the entire system working, and it could stop the whole system. The possibility of locating faults quickly and isolating that part from the other parts of the system would allow the rest of the power microgrid to continue working.

3. Microgrid Model

Specifications :

The micro-grid is a single-phase AC network. Energy sources are an electricity network, a solar power generation system and a storage battery. The storage battery is controlled by a battery controller. It absorbs surplus power when there is excess energy in the micro-network, and provides additional power if there is a power shortage in the micro-network. Three ordinary houses consume energy (maximum of 2.5 kW) as electric charges. The micro-array is connected to the power network via a transformer mounted on a post which lowers the voltage of 6.6 kV to 200 V. The solar power generation and storage battery are DC power sources that are converted to single-phase AC. The control strategy assumes that the microarray does not depend entirely on the power supplied by the power grid, and the power supplied by the solar power generation and storage are sufficient at all times.

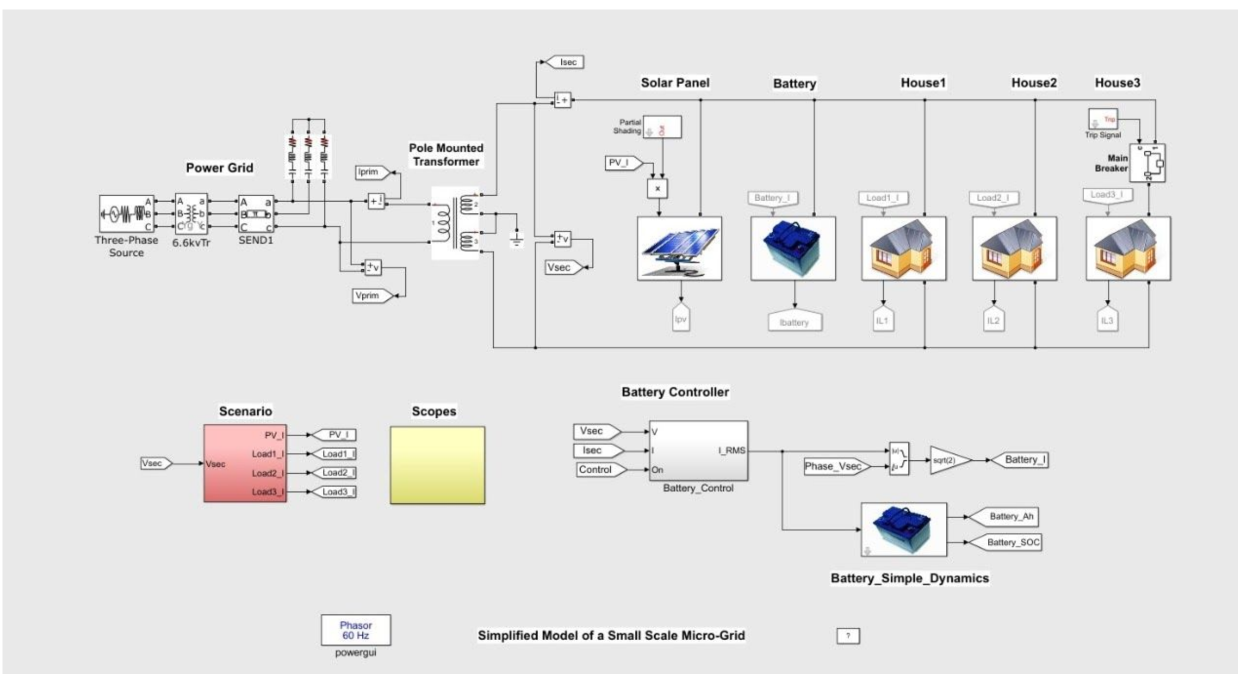


Figure: Simplified Model of a Power Microgrid

Simulation :

From 20h to 4h, the solar power generation is 0 W. It reaches the peak amount (5 kW) from 14h to 15h. As a typical load change in ordinary houses, the amount of electric power load reaches peak consumption at 9h (6,500 W), 19h, and 22h (7,500 W). From 0h to 12h and from 18h to 24h, battery control is performed by the battery controller. The battery control performs tracking control of the current so that active power which flows into system power from the secondary side of the pole transformer is set to 0. Then, the active power of the secondary side of the pole mounted transformer is always around zero. The storage battery supplies the insufficient current when the power of the micro-grid is insufficient and absorbs surplus current from the micro-grid when its power surpasses the electric load. From 12h to 18h, battery control is not performed. SOC (State Of Charge) of the storage battery is fixed to a constant and does not change since charge or discharge of the storage battery are not performed by the battery controller. When there is a power shortage in the micro- grid, the system power supplies insufficient power. When there is a surplus power in the micro-grid, surplus power is returned to the system power. At 8h, electricity load No. 3 of an ordinary house is set to OFF for 10 sec by the breaker. A spike is observed in the active power on the secondary side of the pole transformer and the electric power of the storage battery.

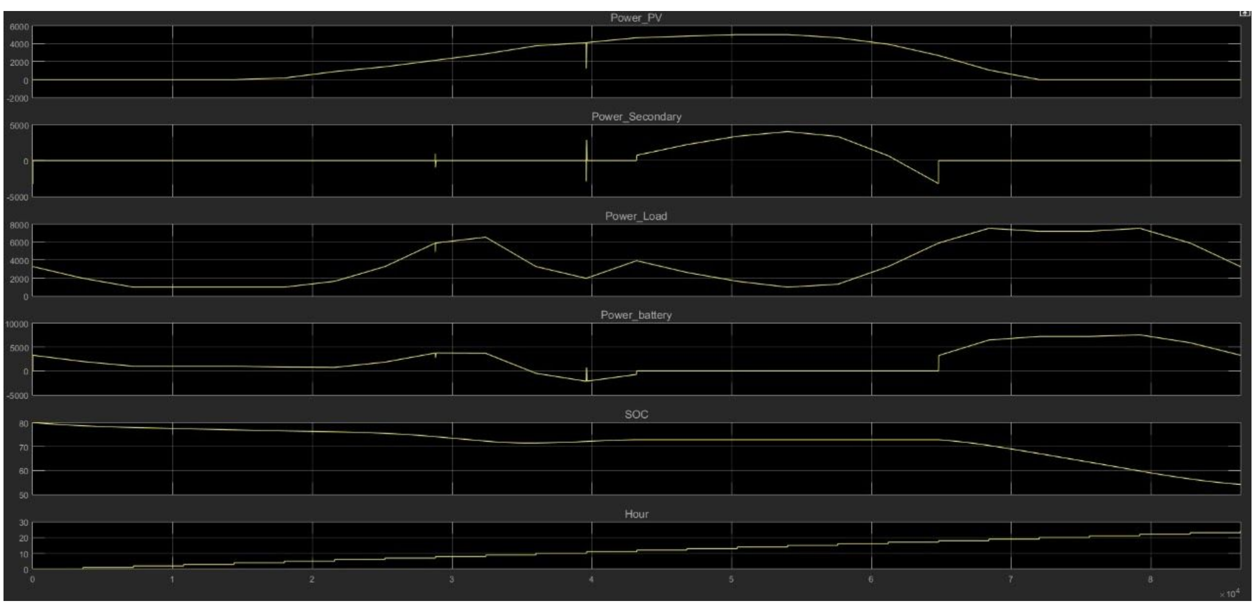


Figure: The graphical outputs of the initial Power Microgrid

4. Faults In A Microgrid and its Detection

Types of Faults :

There are broadly two types of faults which occur in a microgrid, Line to Line Fault and Line to Ground Fault.

The majority of these faults are line to ground fault due to the component or segment failure or lightning. When a short circuit fault happens in the microgrid, the fault resistance tends to zero and the current tends to become infinite.

$$I_f \rightarrow \infty , \quad R_f \rightarrow 0$$

Here I_f is the fault current and R_f is the fault resistance.

Key Idea for detection of faults :

In this case, three circuit breakers are introduced in the circuits before each house as shown in the figure below . They behave as the faults. The properties of breakers are as follows: Breaker Resistance - 0.001 ohm, Snubber Resistance - 1e6 ohm, snubber capacitance - inf. The breakers are initially at state 1 i.e., not activated. Now they are activated one by one for half an hour each time to get the dataset. Each breaker is activated at every hour of the day. So in total we get the total of 96 data points. **Whenever a fault occurs in any part of the system, the values of secondary current I_{sec} and Load Power changes drastically. These changed values play a central role in our model.** At every point secondary current(I_{sec}) and load power value is taken into consideration along with their time of activation. The time of fault plays a major role because of the nature of the circuit.

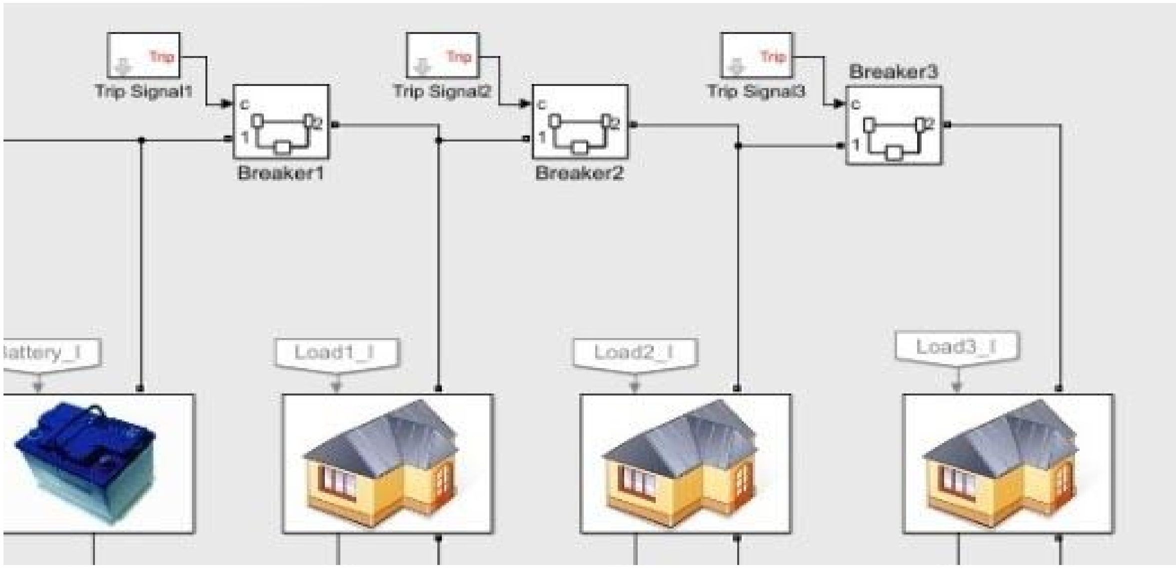


Figure: Three Circuits Breakers are introduced

When the fault is introduced in the circuit a sudden surge of current is seen and a dip in the load power. When the battery controller is working the base of surge is zero but when the battery controller is switched off the base of surge power is different. No fault state graph and the other two graphs can be seen below:

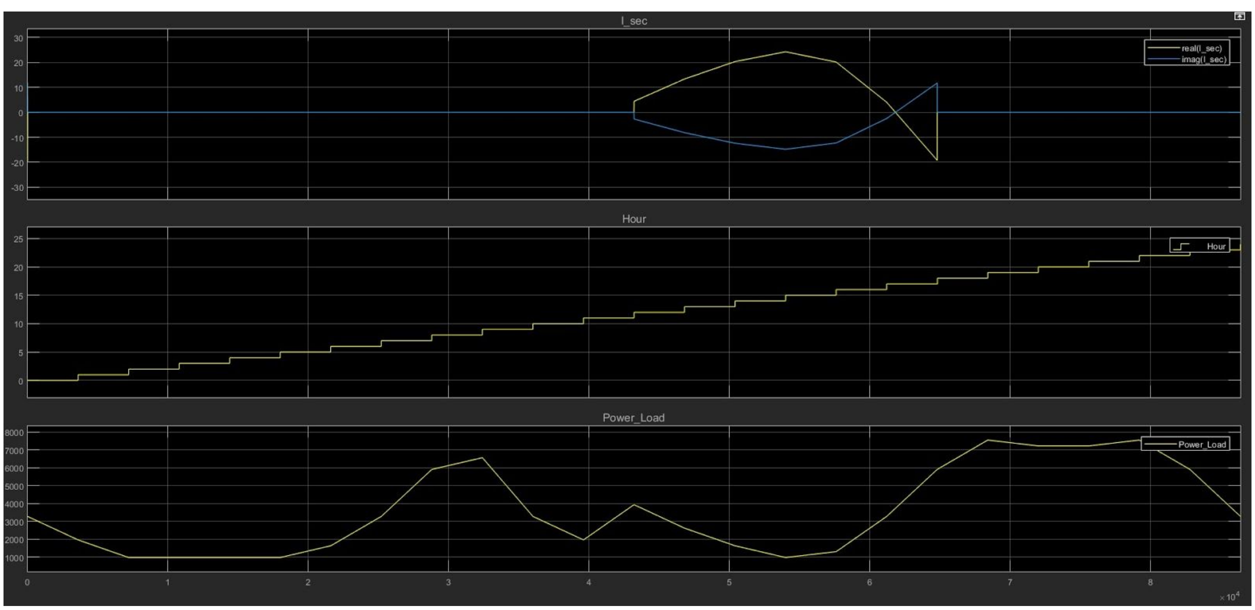
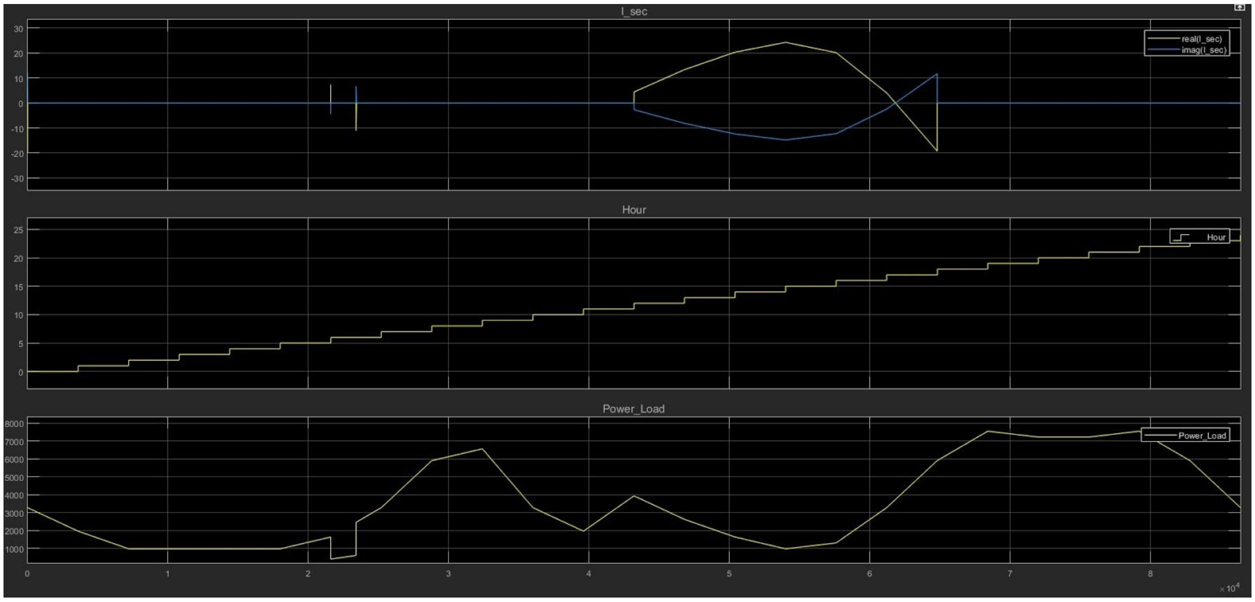
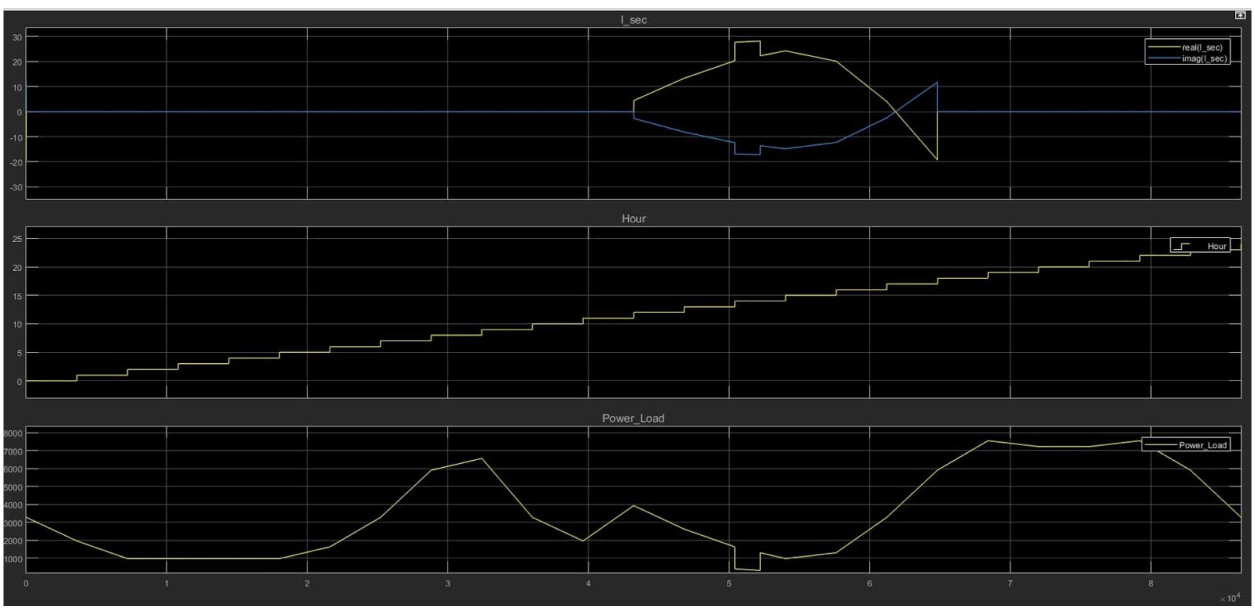


Figure: When all the breakers are in the off state i.e., no fault state



Above graph is obtained when the fault is introduced while the battery controller is working.



Above graph is obtained when the fault is introduced while the battery controller is not working.

Generation of Input Data for ANN Model :

We measure the values of secondary current (I_{sec}), Load power (P_L) consumed by the loads and the time at which this data is measured for a period of 24 hours measuring after every 60 minutes. In this way we get 23 sets of values of all these parameters. We train this dataset (link below) in our ANN model. Now using this trained dataset the location can be known as the fault before the first house or the second house or so on. Here the model consists of three houses, so the dataset obtained is not very big but a large dataset can be obtained by including more loads i.e., houses.

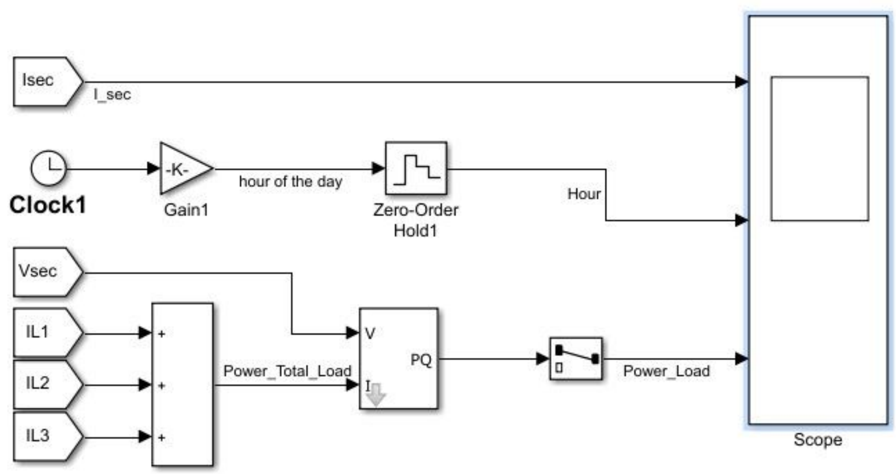


Figure: Measuring the parameters

Raw Dataset : https://tinyurl.com/yayfcfzp

Features to be trained : https://tinyurl.com/y7d7xoqj

5. Solution through ANN Model

The ANN model consisted of an input layer of dimension 92X27, two hidden layers and a final output layer consisting of 4 neurons (softmax layer).

The input consists of of 4 features that are listed as:

1. The current in the circuit.
2. The load power.
3. The time at which breaker was switched on.
4. The result.

** Since the "Time" feature contains only 24 values and is of classification type so we encode it (one hot encoding) thus making the overall inpul features equal to 27.

The input is processed using StandardScaler and then processed for training and also the result is encoded.

```
[ ]  dummy_XX=XX
```

```
[ ]  scaler=StandardScaler()
```

```
[ ]  dummy_XX=scaler.fit_transform(dummy_XX)
```

```
[ ]  from keras.utils import np_utils
```

```
[ ]  encoder = LabelEncoder()
     encoder.fit(yy)
     encoded_Y = encoder.transform(yy)
     dummy_y = np_utils.to_categorical(encoded_Y)
```

Neural Network:

The first hidden layer consists of 16 neurons and has "relu" activation function.

The second hidden layer consists of 8 neurons and also has "relu" activation function.

The final output layer consists of 4 neurons.

```
[ ] def neural_net():
        model = Sequential()
        model.add(Dense(16, input_dim=27, kernel_initializer='normal', activation='relu'))
        model.add(Dropout(0.2))
        model.add(Dense(8, kernel_initializer='normal', activation='relu'))
        model.add(Dense(4, kernel_initializer='normal',activation='softmax'))
        model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
        return model
```

```
[ ] mm=neural_net()
    history=mm.fit(XX,dummy_y,epochs=500)
```

Relu function is defined as:-

$$g(x) = max(0, x)$$

Then finally the model is compiled using “adam” optimizer and the no of epochs were 500 to calculate the accuracy of the model.

To prevent overfitting a dropout layer was added after the first hidden layer.

The full code used in this model can be accessed through this link :
https://tinyurl.com/ydfw9s4r

6. Conclusion

Based on the artificial neural network , the fault detection of microgrid was studied. A small scale modeling of the microgrid including solar panels , battery energy storage system, loads and AC grid is simulated in MATLAB. A sudden change in the value of secondary current $\mathbf{I}_{sec}$ and the load power $\mathbf{P}_{L}$ is the basis for the algorithm that detects the fault location. Here we observe the spikes in the graph of $\mathbf{I}_{sec}$ as the faults .These faults are generated manually by switching on each of the circuit breakers at various moments of a day . Also the faults were studied by keeping as well as isolating the battery controller. Having generated the data at various times of a day and training the dataset in ANN fetched a decent accuracy of (70%~80 %). So having new data of power, $\mathbf{I}_{sec}$ and time of the day , we can predict if there is a fault or not , and if there is , the location of the fault can be determined pretty accurately.

```
92/92 [==============================] - 0s 222us/step - loss: 0.8007 - accuracy: 0.7826
Epoch 488/500
92/92 [==============================] - 0s 183us/step - loss: 0.8425 - accuracy: 0.6957
Epoch 489/500
92/92 [==============================] - 0s 186us/step - loss: 0.8442 - accuracy: 0.7174
Epoch 490/500
92/92 [==============================] - 0s 213us/step - loss: 0.7975 - accuracy: 0.7717
Epoch 491/500
92/92 [==============================] - 0s 182us/step - loss: 0.8237 - accuracy: 0.7065
Epoch 492/500
92/92 [==============================] - 0s 200us/step - loss: 0.8246 - accuracy: 0.7283
Epoch 493/500
92/92 [==============================] - 0s 190us/step - loss: 0.7893 - accuracy: 0.7391
Epoch 494/500
92/92 [==============================] - 0s 180us/step - loss: 0.8570 - accuracy: 0.6848
Epoch 495/500
92/92 [==============================] - 0s 163us/step - loss: 0.7841 - accuracy: 0.7609
Epoch 496/500
92/92 [==============================] - 0s 179us/step - loss: 0.8454 - accuracy: 0.6630
Epoch 497/500
92/92 [==============================] - 0s 204us/step - loss: 0.8512 - accuracy: 0.6957
Epoch 498/500
92/92 [==============================] - 0s 195us/step - loss: 0.7856 - accuracy: 0.7609
Epoch 499/500
92/92 [==============================] - 0s 193us/step - loss: 0.7872 - accuracy: 0.8043
Epoch 500/500
92/92 [==============================] - 0s 180us/step - loss: 0.8159 - accuracy: 0.7826
```

Figure : 78.26% accuracy in prediction and location of fault