# Recurrent Neural Networks for Voltage Control in the Case of Small Modular Reactor Integration in a High Renewable Energy Isolated Grid

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## 1. Introduction

Voltage control is desirable for voltage stability which is the ability of an electrical power system to maintain voltages within fixed tolerable ranges at every single bus before and after a system disturbance. In the quest of achieving the target of net-zero carbon emissions by 2050, there is a significant uptake of renewable energy across the globe [1]. However, most renewable energy sources are intermittent in nature. Their power grids fall short of the capacity to quickly synchronize and compensate for reactive power required by changes in dynamic loads, and in addition, they suffer from unpredictable voltage and frequency fluctuations. The modularity and enhanced safety features of the SMR [2], gives it the ability to be connected near load centers and in isolated grids due to their load-following capability. However, SMR deployed in an isolated grid may experience frequent tripping if voltage control is not established. Previous studies have shown the application of artificial neural networks (ANN) and the impact of installation of on load tap-changers (OLTC) on voltage control of base-load power plants connected to an unstable grid via an infinite bus [3]. Voltage control through the main transformer OLTC requires an accurate method with a multi-factor consideration approach. In this case, Artificial Intelligence (AI), through machine-learning by the recurrent neural networks (RNN) modelling, was applied for tap-changer setting control to achieve voltage stability in a peak-load power plant connected to the grid through a finite bus.

## 2. Methods and Results

In this section the Korea's System-integrated Advanced ReacTor (SMART) SMR-107MWe which has an approved design [1] was selected as a representative of SMR technologies with load-following capability that can be deployed in similar scenarios.

### *2.1 Electrical Power System Configuration for SMR*

The main and auxiliary power system configuration was optimally modelled with voltage control being implemented through the main transformer OLTC.
The power system design was made such that the major equipment and buses conform to the requisite standard for preferred power supply (PPS) [4]. The proposed configuration is as shown by the schematic power system illustrated in Fig. 1. The switchyard voltage level of 154kV was selected from standard transmission voltages in the Korean grid code. This will be used in the simulation as representative of any transmission voltage levels across the globe that can be linked to other renewable energy sources.

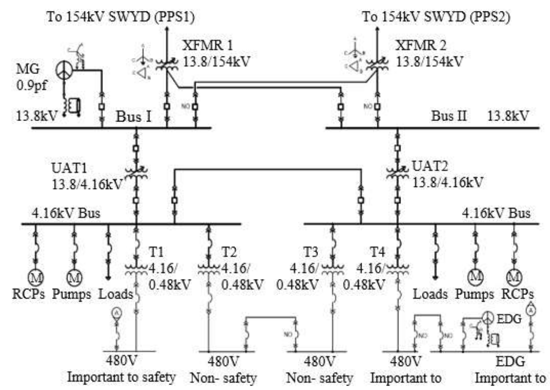


Fig. 1. Proposed SMART SMR system configuration

The designed SMART SMR model power system comprises of two main transformers (with OLTC) meant to step up generation voltage from 13.8kV to 154kV. The two transformers provide the paths for the preferred power supply transformation. Redundancy was achieved such that either of the transformers can be used interchangeably by an automated switching operation. The auxiliary power system is composed of two 13.8kV/4.16 kV transformers that operate in parallel and hence provide for redundancy in the medium voltage level. The low voltage network is further divided into important to safety and non-safety buses which are also interlinked to provide multiple backup configurations for voltage stability and defense in depth for the system. The emergency diesel generator is on the low voltage level where safety related loads are connected.

### *2.2 Recurrent Neural Networks*

This is a deep learning algorithm tailored to deal with sequential data. This features makes it good for learning and prediction. The advanced RNN variant used in this study is the long short term memory (LSTM) which has gates that regulate the flow of information. Forget gate decides how much of the previous data will be forgotten and how much will be used in next steps. The result of this gate is typically in the range of 0-1 where "0" forgets the previous data, and "1" uses the previous data. The input gate works as an input to the cell state while the output gate contains information on previous inputs and is used for prediction.

Fig. 2. shows the structure of an advanced RNN module (LSTM).

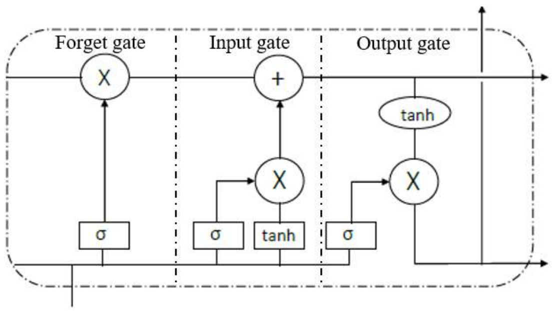


Fig. 2. LSTM Model of RNN

*2.3 Recurrent Neural Network Modelling*

The model was made using an advanced RNN model (LSTM). Root mean square error (RMSE) was used as the evaluation metrics. Fig. 3. shows the flowchart diagram of the prediction model.

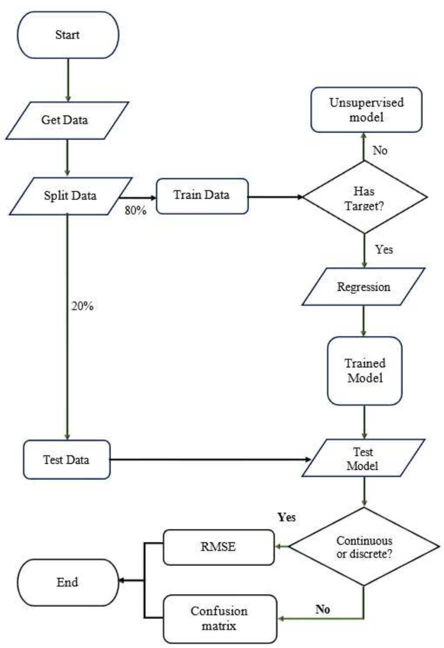


Fig. 3. Prediction Model Flowchart

*2.4 SMR Main transformer OLTC Control*

The OLTC is conventionally designed to keep the voltage on the secondary side of a transformer within a preset range. It is a motor driven mechanism that adjusts the transfer ratio of voltages according to the preset values. The voltage control desired in SMART SMR integrated in an isolated gird is that which takes care of the generator bus and the grid with special consideration on the dynamic active and reactive power components in the system. Therefore, accurate reference voltage must be selected in order to mitigate voltage excursions due to various factors including change in loading and other system disturbances. Modelling of the renewable energy grid under study was done on the standard IEEE 5 bus system with consideration of the IEEE 1547-2018 [5], standard which provides for the range of overvoltage (1.10) p.u and undervoltage of 0.88 p.u for the case of renewable energy integrated to the grid. Fig. 4. shows a typical layout of an advanced tap-changer configuration.

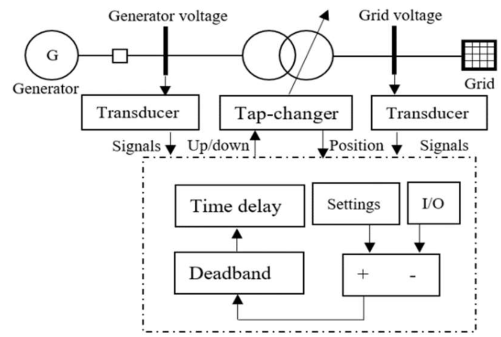


Fig. 4. Advanced OLTC tap-changer configuration

*2.5 Optimal OLTC Control Method Selection*

The control method is selected by comparative analysis of the percentage tap settings obtained from the prediction by RNN and the electrical transient analyzer program (ETAP) load flow analysis. An RNN model was build based on simulation data with percentage tap settings as the target and the training features included active power, reactive power and grid voltage assuming a finite bus. The model mimics the daily loading dynamics by varying the load and the renewable energy sources (RES) generation contribution with the assumption of renewable energy providing only the active power. This was done with reference to the generator reactive power capability curve which provides for operation between p.f 0.85 lagging to 0.90 leading in order to safeguard the generator from heating and mal-operation beyond its rated limits. Sampled simulation data was as shown in Table I.

Table I: Voltage Control when Connected to a Finite Bus

| %Load | Demand P(MW) | Demand Q(Mvar) | RES P(MW) | SMR P(MW) | SMR Q(Mvar) | Vgrid (p.u) No T/C | Vgrid (p.u) With T/C | ETAP %TAP |
|---|---|---|---|---|---|---|---|---|
| 150.0 | 134.0 | 85.5 | 63.6 | 70.4 | 85.5 | 0.9270 | 1.0020 | 8.125 |
| 148.0 | 131.0 | 83.6 | 63.6 | 67.3 | 83.6 | 0.9289 | 0.9986 | 7.500 |
| 145.0 | 127.9 | 81.7 | 63.6 | 64.3 | 81.7 | 0.9308 | 1.0010 | 7.500 |
| 143.0 | 125.9 | 80.4 | 64.1 | 61.8 | 80.4 | 0.9321 | 1.0020 | 7.500 |
| 141.0 | 123.8 | 79.1 | 65.0 | 58.8 | 79.1 | 0.9334 | 0.9975 | 6.875 |
| 138.0 | 120.8 | 77.2 | 65.4 | 55.4 | 77.2 | 0.9352 | 0.9995 | 6.875 |
| 136.0 | 118.7 | 76.0 | 65.7 | 53.0 | 76.0 | 0.9365 | 1.0010 | 6.875 |
| 133.0 | 115.7 | 74.1 | 66.0 | 49.7 | 74.1 | 0.9383 | 0.9970 | 6.250 |
| 125.0 | 107.5 | 69.0 | 65.7 | 42.1 | 69.0 | 0.9431 | 1.0020 | 6.250 |
| 120.0 | 102.4 | 65.9 | 66.0 | 36.4 | 65.9 | 0.9460 | 0.9992 | 5.625 |
| 110.0 | 092.2 | 59.5 | 65.5 | 26.7 | 59.5 | 0.9518 | 0.9994 | 5.000 |
| 085.0 | 066.7 | 43.7 | 64.5 | 02.2 | 43.7 | 0.9655 | 1.0020 | 3.750 |

Table I shows the contribution of RES and SMR in meeting the grid demand as the load changes by various percentages. The values of grid voltage before and after OLTC action are also shown alongside the percentage tap settings. The table also shows the intermittent nature of RES. Fig. 5. shows the effective voltage control by the OLTC. The voltages were initially operating beyond the stability limit of ±5%. However, the action of the tap-changer corrected the voltages to operate near unit p.u values where stability is high. The effective tap setting per load change with time is as shown in Fig. 6.

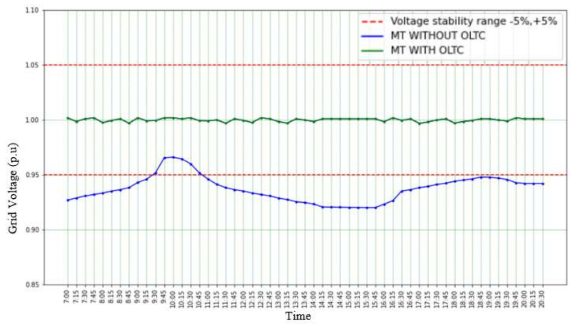


Fig. 5. Effective voltage p.u. control by OLTC action


Fig. 6. Percentage tap settings with change in demand

Fig. 7. shows the load following operation of the SMR. The RES provides only active power and does not perform any load following operation. The SMR meets the full load demand whenever the RES goes zero power output like in the evening for the case of photovoltaic cells.

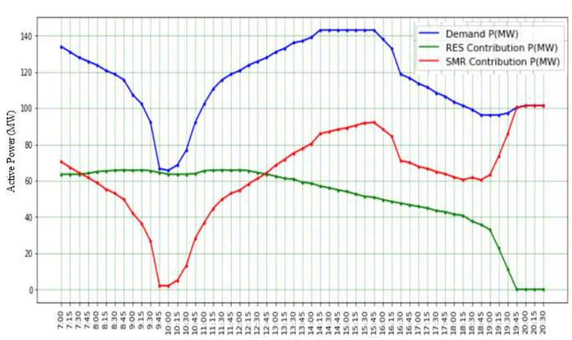


Fig. 7. Load profile showing SMR load following operation

The RNN model was built using the LSTM configuration as shown in Fig. 8.

```
Model: "sequential_44"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 lstm_89 (LSTM)               (None, 5, 128)            66560

 lstm_90 (LSTM)               (None, 128)               131584

 dense_42 (Dense)             (None, 1)                 129

=================================================================
Total params: 198,273
Trainable params: 198,273
Non-trainable params: 0
```

Fig. 8. RNN training and prediction model summary

Fig. 9. shows the peformance evaluation of the trained RNN model to acertain the applicabilty of the model in robust percentage tap-settings predictions.The mean absolute error (MAE), mean square error (MSE), and the RMSE were used as the metrics for evaluation.

```
MAE........: 0.7661084532737732
MSE........: 0.03616354614496231
RMSE........: 0.19016715317047345
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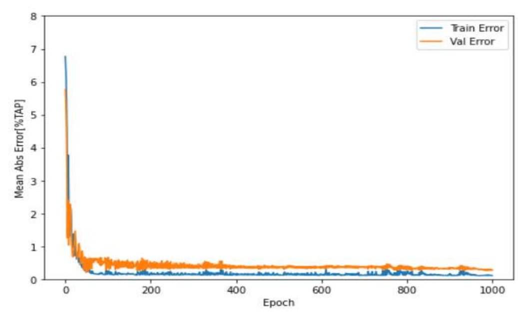


Fig. 9. Performance evaluation of the trained model

The model was then used for prediction of percentage tap settings for a similar data set with the ETAP software that had the upper band and lower band setting of 0.3125 percent , and increamental tap step of 0.625 percent in order to draw a comparison between the two methods. The RNN model prediction results superimposed on the ETAP plot, exhibiting similarities as shown in Fig. 10.


Fig. 10. RNN predictions compared to ETAP %tap settings

In the case of finite bus, voltage control was achieved by tap-changer action and reactive power compensation so as to maintain steady grid voltages with varying demand. The target data was obtained from simulations since it was impossible to carry out a practical experiments for this study. The modelled renewable energy grid bus voltage was used as reference for the simulations of tap-changer response.

When the load in a power system was increased, the voltage decreased and vice-versa. Reactive power demand indirectly results in alteration of the excitation winding of the generator which has limits of operations within the defined generator D-curve. Installation of on load tap-changing transformers takes care of coarse voltage deviations. More so, optimal power flow calculations can be employed to define voltage for all regions in the system. The use of RNN was found to be a precise method for OLTC control to mitigate voltage challenges of high renewable energy penetration in the isolated grids. Upon comparison, the RNN percentage tap-settings superimposed on the ETAP OLTC tap-settings showing the degree of accuracy in prediction as shown in Fig.10.

## 3. Conclusion

This paper recommends the adoption of the Artificial Intelligence based recurrent neural network for the OLTC control method in SMR for a fine and seamless integration to isolated grids with high renewable energy. Load following capability of SMR was assumed as required. The OLTC control method was able to demonstrate the ability to mitigate voltage excursions in a finite bus by providing steady percentage tap-changer settings using a number of parameters that include active power, reactive power, and voltage components as opposed to conventional OLTC control that checks the reference voltage magnitudes only. This addressed the issues of voltage instability in high renewable energy isolated grids.

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