Proceedings of the 2nd International Conference on Mathematical Physics and Computational Simulation
DOI: 10.54254/2753-8818/39/20240591

Machine learning based feedforward voltage control for buck converters in envelope tracking applications

Ruixuan Ying

Shanghai World Foreign Language Academy, Shanghai, China

ruixuanying 2025@stu.swfla.org

Abstract. Tracking the voltage envelope of 5G base station power supplies poses a significant long-term challenge. To achieve fast and accurate envelope tracking, an efficient and high-frequency power electronics circuit and an excellent voltage controller are essential. This paper presents a novel machine learning (ML) based feedforward control method for precise voltage reference tracking. The method is exemplified using a standard buck converter in both continuous conduction mode (CCM) and discontinuous conduction mode (DCM). A feedforward neural network (FNN) is trained to capture non-ideal and non-linear effects in real circuits. An automated data collection system, developed with MATLAB and Simulink, facilitates data acquisition and model training process. The trained FNN predicts the duty cycle for the buck converter to generate the targeted output voltage and output power. A simulation model is built to validate the effectiveness of the FNN controller in envelope tracking applications.

Keywords: machine learning, feedforward neural network, buck converter, voltage control, continuous conduction mode, discontinuous conduction mode

1. Introduction

Wide deployment of 5G base stations has become a major concern in the world. Due to their required larger quantity and higher energy consumption compared to 4G stations, these base stations demand a significantly higher total energy. Compared to 4G technology, 5G not only increases power consumption by nearly three times, but also increases the number of 5G base stations exponentially due to the attenuation of coverage range. The full load power consumption of a single 5G base station system from mainstream manufacturers is about 3.5-4kW. According to statistics, the average daily power consumption of existing 5G micro base stations in China is about 65kWh. If calculated based on the electricity price of 1 RMB per kWh, the annual electricity expenditure of only 5G base stations nationwide will reach 76.3 billion RMB, which is a heavy burden for operators. Therefore, efficient energy utilization appears to be important and energy loss has emerged as a persistent concern in the development of 5G technology.

The traditional power supply architecture always provides a constant large voltage to the 5G base station. However, as the power required by appliances is not always constant, setting a constant voltage input would create a considerable amount of energy loss during low-power working periods. Addressing this issue commonly involves employing the technique of envelope tracking (ET) shown in fig. 1. Instead of setting a constant input voltage for antenna arrays, ET technology continuously adjusts the

DOI: 10.54254/2753-8818/39/20240591

input voltage according to the voltage and power demand, effectively controlling input voltage at minimal required levels[1]. Central to this approach is the use of a high-speed step-down dc-dc converter that can track the voltage demand promptly while still maintaining high efficiency for energy management and distribution.

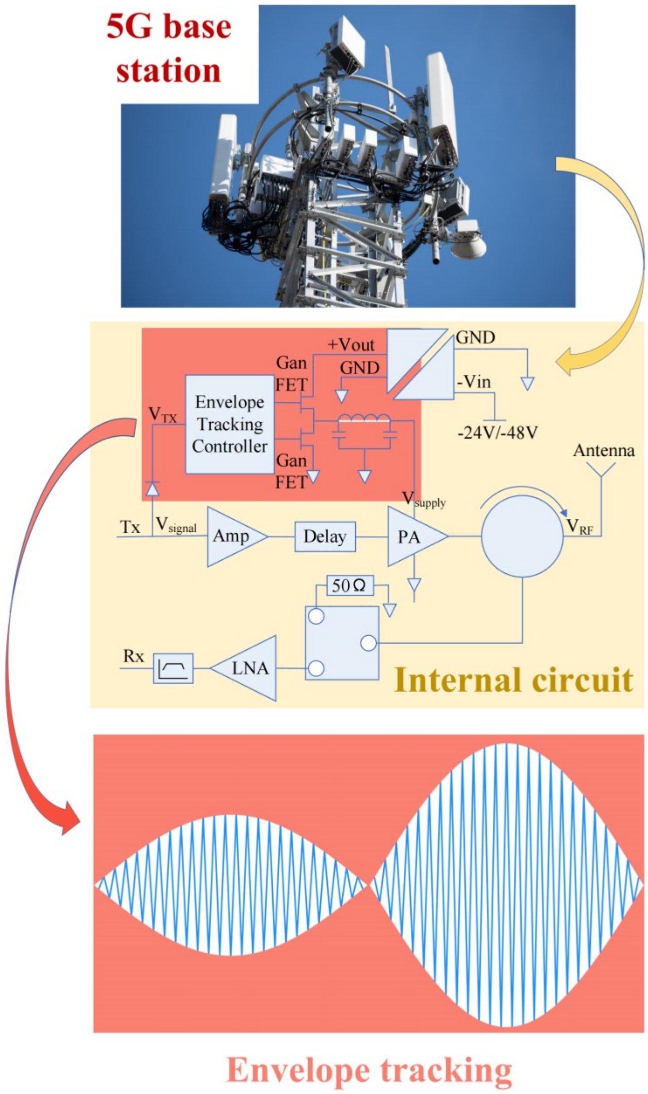

Figure 1. A schematic map of envelope tracking method presented in a 5G base station. In the base station, an envelope tracking controller is installed before a power amplifier to track the voltage input.

Within the power converter realm, the buck converter stands as a fundamental element, performing the function of voltage step-down. The basic concept of buck converter is to utilize the properties of inductor and capacitor to reduce the input voltage by frequently switching the MOSFET component within the converter circuit. The output voltage would oscillate between a certain range of values which can be adjusted by changing parameters of the converter components. Its optimization holds substantial importance in domains such as data centers and battery chargers, where dynamic and diverse power demands prevail. To allow buck converter fully utilized within the situation of 5G base station power supply, the control parameters such as duty cycle must be constantly changed to adjust the output voltage. Normally, the feedback control method is used in the adjustment process. The control parameters are frequently alternated according to the relative deviation between desired and actual output voltages. This results in an output voltage much closer to the targeted value with multiple switching cycles. However, the feedback control method may not be suitable for 5G base station applications. As output voltage constantly changes, the feedback controller may not track the reference voltage precisely and the created bias leads to more power loss. Therefore, a feedforward control method is more suitable in this situation, where the control parameters are pre-set based on the desired output voltage and power, which means multiple parameter adjustments are not required. Feedforward control can also be combined with feedback control for higher system stability. To facilitate this operation, a reliable and fast feedforward controller should be selected.

Machine learning (ML), with its ability to acquire system characteristics and make real-time decisions, enhances the control and operation of buck converters. Machine learning has been proved effective in the control of power electronics, capturing hidden parameters and effects in the real circuit[2]. Utilizing the potential of advanced machine learning algorithms like neural networks aims to achieve fast and precise voltage control. By using a large amount of data collected in the buck converter simulation, a feedforward neural network (FNN) can be trained with the desired voltage and power as model inputs, and the corresponding duty cycle as model outputs. This paper also demonstrates an automated simulation data collection system designed to expand the data set, thereby enhancing the prediction accuracy of the buck converter control parameters. [3]

2. Buck Converter Modeling with Different Operation Modes

The main circuit focused in this paper is the buck converter shown in fig. 2, one type of step-down converters. It is a DC-DC converter that converts the input voltage to a lower output voltage required by loads of a system. Buck converter involves switching on and off a MOSFET with high frequency, and utilizes the properties of an inductor and a capacitor to store temporary energy in the circuit and step down the voltage. The energy is frequently stored and released when the MOSFET is turned on and off, producing a constant DC output voltage with small ripples. This characteristic provides a significantly lower power loss compared with traditional and simpler step-down circuits such as low dropout regulator (LDO) [4], which directly converts extra voltage to heat and gets dissipated. Therefore, buck converter is more commonly used in voltage regulators inside precise circuits such as computers and base stations which require accurate output voltage and low power loss.

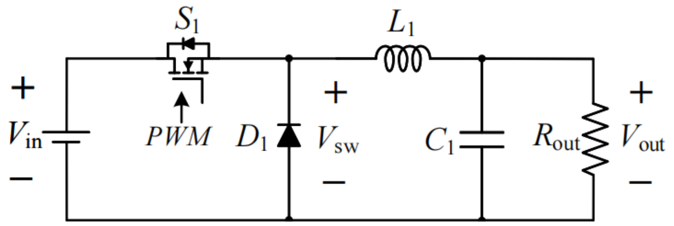

Figure 2. A buck converter circuit diagram. Buck converter is commonly used in voltage adjustment in electronic devices such as computers or cellphones due to its low heat loss and high precision. It is also utilized in the internal circuit of 5G base station. Therefore, buck converter is targeted as the step-down converter modelled in this paper.

2.1. Continuous Conduction Mode (CCM)

For an ideal buck converter, the relationship between input voltage and output voltage can be calculated with the help of an average circuit model illustrated by fig. 3 for current change and fig. 4 for voltage change. In phase 1, the switch S_1 turns on during the time interval $\Delta t_1 = DT$ and the inductor is connected to both input and output, thus the voltage on the inductor $V_1 = V_{in} - V_{out}$. In phase 2, the diode D_1 turns on during the time interval $\Delta t_2 = (1 - D)T$ and the inductor is connected to both input and output, thus the voltage on the inductor is $V_2 = -V_{out}$.

DOI: 10.54254/2753-8818/39/20240591

$$\begin{cases} \Delta i_1 = \frac{V_1}{L1} \cdot \Delta t_1 \\ \Delta i_2 = \frac{V_2}{L1} \cdot \Delta t_2 \\ \Delta i_1 = -\Delta i_2 \end{cases} \tag{1}$$

Meanwhile, the increased current during phase 1 and decreased current during phase 2 should be equal to keep a stable system.

Then the relationship between the duty cycle and the output voltage in CCM can be expressed as:

$$D = \frac{V_{out}}{V_{in}} \tag{2}$$

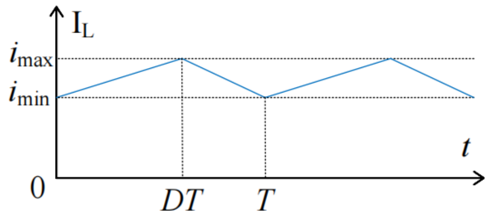

Figure 3. The current change of a buck converter during CCM

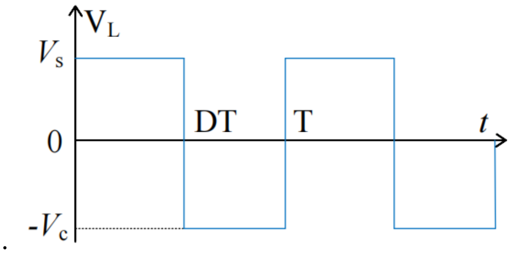

Figure 4. The voltage change of a buck converter during CCM.

2.2. Discontinuous Conduction Mode (DCM)

In some practical cases, the amount of energy required by the load is too small. In this case, the current through the inductor falls to zero during part of the period. The difference to CCM mode of buck converter is that the inductor is completely discharged at the end of the commutation cycle. This state is called a discontinuous conduction mode (DCM). The current and voltage changes under DCM can be illustrated by fig. 5 and fig. 6 respectively.

As the current across the inductor current is reduced to zero, the value of the voltage across the inductor is also reduced to zero value while $V_c = V_o$ during the entire cycle.

For the time duration, $0 \leq t \leq T_{on}$,

$$I_{L+}(t) = \frac{V_s - V_o}{L} t \tag{3}$$

As the value of the peak inductor current occurs at $t = T_{on}$,

$$I_{max} = \frac{V_s - V_o}{L} T_{on} = \frac{V_s - V_o}{L} t \tag{4}$$

For the time duration, $T_{on} \leq t \leq T_x$,

$$I_{L-}(t) = \int_{T_{on}}^{t} -\frac{V_c}{L} dt + I_{max} = \frac{V_c}{L}(T_{on} - t) + \frac{V_s - V_o}{Lf} \tag{5}$$

At $t = T_x$, current reduces to zero value,

$$0 = \frac{V_c}{L}(T_{on} - T_x) + \frac{V_s - V_o}{Lf} \tag{6}$$

$$T_x = D\frac{V_s}{fV_o} \tag{7}$$

Compared to the continuous condition, the amount of energy needed by the load is lesser in the discontinuous condition.

It is considered that the converter is operated in the steady-state. Thus, the energy in the inductor remains the same at the start and at the end of the cycle. The volt-time balance condition can also be applied here.

The above equation can also be derived using the inductor volt-second balance condition as

$$(V_s - V_c)T_{on} + (-V_c)(T_x - T_{on}) = 0 \tag{8}$$

$$(V_s - V_c)DT + (-V_c)(T_x - DT) = 0 \tag{9}$$

$$T_x = V_s\frac{D}{fV_o} \tag{10}$$

For the time duration, $T_x \leq t \leq T$,

$$I_{L0}(t) = 0 \tag{11}$$

From figure. 6, it is clear that the average value of the inductor current is equal to the area under the load current curve divided by T.

$$I_{avg} = \frac{\frac{1}{2}T_x I_{max}}{T} \tag{12}$$

For the DC supply,

$$I_{avg} = \frac{V_o}{R} \tag{13}$$

Hence,

$$\frac{V_o}{R} = \frac{V_s(V_s - V_o)D^2}{2LV_o f} \tag{14}$$

The duty cycle ratio for the DCM in the case of the buck converter is

$$D = V_o\sqrt{\frac{2Lf}{RV_s(V_s - V_o)}} \tag{15}$$

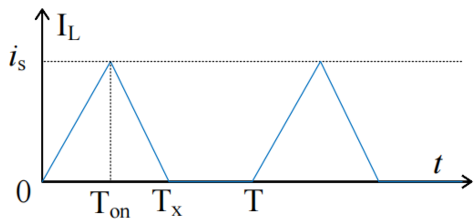

Figure 5. The current change of a buck converter during DCM.

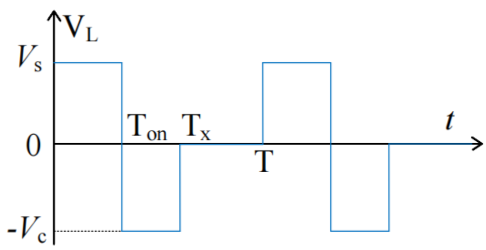

Figure 6. The voltage change of a buck converter during DCM.

The output voltage is determined by a set of factors related to the buck circuit. The main factor is the duty cycle, which is the time proportion of the MOSFET being turned on. Practically, a higher duty cycle would typically lead to a higher output voltage. There are also other factors, such as the equivalent resistance of the inductor and the capacitor, the turn-on resistance of the MOSFET, the switching loss of the MOSFET, the forward voltage drop of the diode, the reverse recovery loss of the diode, etc [5]. Those parasitic effects inherently exist in the circuit and greatly influence the output voltage. Only duty cycle can be controlled because these values are fixed when the circuit is designed and built. Besides, output resistance or output power is also considered an important factor that may affect the output voltage due to voltage drop on parasitic components, hence output power is also considered in the control framework.

3. Automated Data Acquisition System

A large amount of high-quality data is essential to successful machine learning training. As shown in fig. 7, to collect data on different values of duty cycles that are required to generate a specific output voltage under a particular output resistance, a digital simulation of the buck converter is conducted via Simulink, a MATLAB-based circuit simulator. There are several advantages of utilizing Simulink to produce virtual data of buck converter. The parameters of the components can be adjusted freely by MATLAB code in the outer layer of the Simulink model, which helps to produce various sets of data with different inputs. Also, the data generated from circuit simulation can be directly transferred to MATLAB for further processing and neural network training.

Before running the simulation, two sets of values are prepared as the inputs to the circuit: one is the duty cycle of the converter from 0.05 to 0.50 with 0.05 interval, while the other is the output resistance from 0.5*Ω* to 50.0*Ω* with 0.5*Ω* interval. The sets are generated via MATLAB code, which are combined to form 10000 data points, and all of them are fed into simulation respectively. The other parameters of the buck converter such as the components and the input voltage are kept constant. Then, the simulation is run to generate sets of output current and voltage within the first 5e-3s. At the beginning of the simulation, the output voltage is experiencing an unstable state, and then reaches a steady state. To determine when the steady state starts, the average output voltage during each period is calculated, then the average values of the last three periods are compared. A difference within 0.7% indicates a steady state, and the final average output is recorded as the result of this set of input. Through this process, a final average output voltage can be produced for every input set of the simulation.

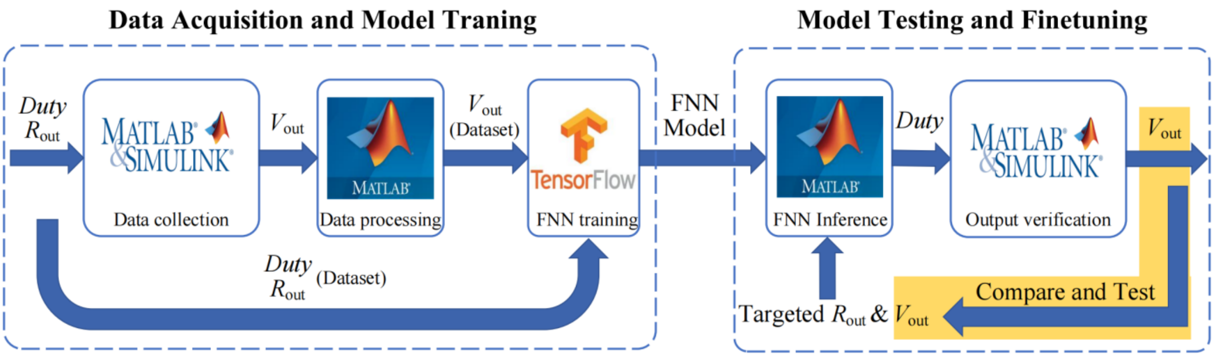

Figure 7. The fowchart of the proedure of training a machine leaning model to predict durty cycle of a buck converter. In the data acquition and mode training section, a range of duty cycle and output resistance values are generated and imported into a pre-modelled buck converter in Simulink to obtain a setof output voltage. Then the data set is processed and put ino a machine leaning model (a feedforward neural network molel, in this paper) via Tensorfiowfor traning. In the model testing and finetuming secion, the machine leaming model is given a set of target output resistance and ouput volage to obtainpredicted duty cycle values, which are then imported into buck converter simulation.The output volage values is then compared with target values to testthe_validity of prediction made by the model.

4. Machine Learning Methods in Converter Control

Being popular for prediction and estimation, machine learning method is commonly utilized to produce outputs based on a large training data set as its reference. Compared with traditional prediction methods that use prepared formulae, machine learning method is able to adapt practical situations as the machine learning model is trained by data acquired from real scenarios rather than ideal relationship between physical quantities. Therefore, machine learning method is expected to have a greater precision than traditional methods in predicting duty cycle used in a buck converter.

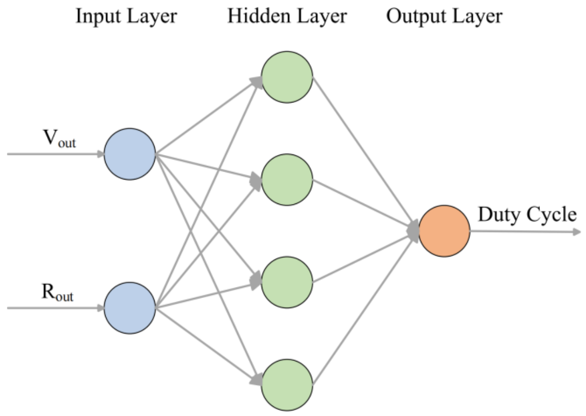

Figure 8. A demonstration diagram of a feedforward neural network.

In the case of buck converter model, there are two inputs in the model: the output voltage and the output resistance. These two value sets are chosen from the training data set obtained from buck converter simulation as the inputs and are imported into the model. Then, after several hidden layers of nodes, a single output of duty cycle is obtained. During training, the predicted duty cycle is frequently compared with the duty cycle in the training data set to check the validation of prediction. An optimal trained model should have an overall lowest validation error when using the training data set as the input and desired output.

The machine learning model used in this paper is a feed-forward neural network. In an FNN model shown in fig. 8, information is flown through layers of nodes in one direction only, allowing input information processed through hidden layer to produce output value. Single-direction flow of information indicates the convenience of training and utilization of FNN, which is suitable for electric circuit prediction that would commonly use large training set of data.

Before the data generated from the simulated buck converter is imported into the FNN model, the process of normalization is undergone, which is to convert all input and output data into a common range of numbers. This step is necessary as normalized training set which eliminates range difference usually gives out a better training result. The normalization method used in this paper is min-max feature scaling, which is to convert all values into numbers in range from 0 to 1. The normalized value is obtained through the following equation:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{16}$$

Several parameters of the FNN model is set before the model is trained. The model has a hidden layer size of 8, a maximum epoch number of 1000 and a learning rate of 0.1. It uses mean square error as its cost function and Levenberg-Marquardt algorithm as its optimizer.

The training data set, obtained from Simulink model and pre-processed by MATLAB code, is imported into the FNN model, with output voltage and resistance set as the inputs and duty cycle set as the output. For the data set, 70% is set as the training set of the model, 15% is set as the validation set for model selection, and 15% is set as the test set for model validation. The division of data set is all random to make sure the rigidity of the training process.

DOI: 10.54254/2753-8818/39/20240591

After model training is finished, the original data set as a whole is given to the FNN model to predict the duty cycle required for a particular output voltage and resistance. The predicted values are then compared with the desired value to test if the model successfully predicts the duty cycle required for each set of circuit condition.

The histogram in fig. 9 shows an overall accumulation of percentage error around 0% and an overall range from -4% to 4%, showing a low percentage error for most data during validation test. The result shows that the model has an appreciable fitting with the training data set. Besides, the training data acquisition is successful as it helps the model to perform well in prediction.

5. Simulation Verification

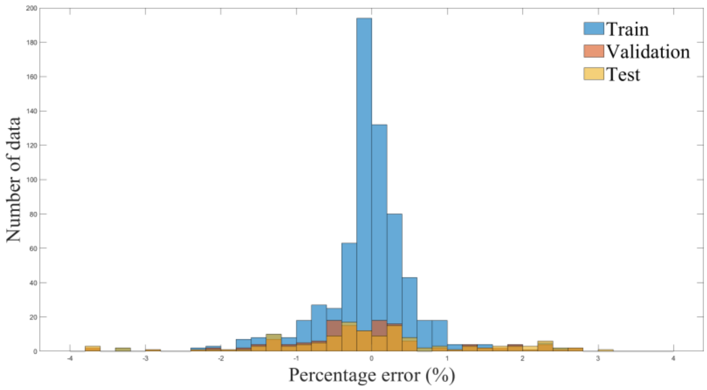

Figure 9. The error histogram of the FNN model, generated using the training set, validation set and test set used during model training.

To test the precision of prediction made by the FNN model, the predicted values of duty cycle are imported back to the buck converter simulation. Then a set of output voltage is generated as the actual output voltage values that are produced by prediction of the model. Then the actual output voltage values are compared with the desired values obtained previously during data acquisition section to obtain a set of percentage error. As shown in the histogram in fig. 10, the percentages are mostly concentrated in the range from -0.8% to 0.8%, showing an overall high precision of the prediction.

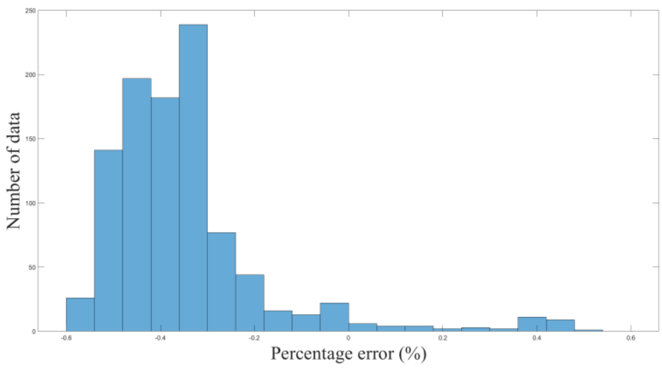

Figure 10. The error histogram of output voltage of the prediction of duty cycle based on training data set.

Besides, the capability of predicting continuous change in voltage output of the FNN model is tested in order to match the requirement of envelope tracking. To generate the result, a arbitrary polynomial consisting of several sinusoidal functions is determined as the desired output voltage. Then a section of the polynomial (with range larger than its smallest period) is chosen and the corresponding output voltage values are imported into the FNN model with a fixed output resistance. Then a set of predicted duty cycle is obtained which is then put into the buck converter simulation to generate output voltage values. This set of values is converted into a curve, with the original output voltage expression converted into another curve.

As shown in the lower diagram in fig. 11, despite some accidental sharp transitions, the error curve fluctuates between -1% to 0.8%, showing a consistence of the actual output voltage fitting the target output voltage. As shown in fig. 12, most of the percentages lie in the range from -0.8% to 0.8%, showing a relatively high accuracy.

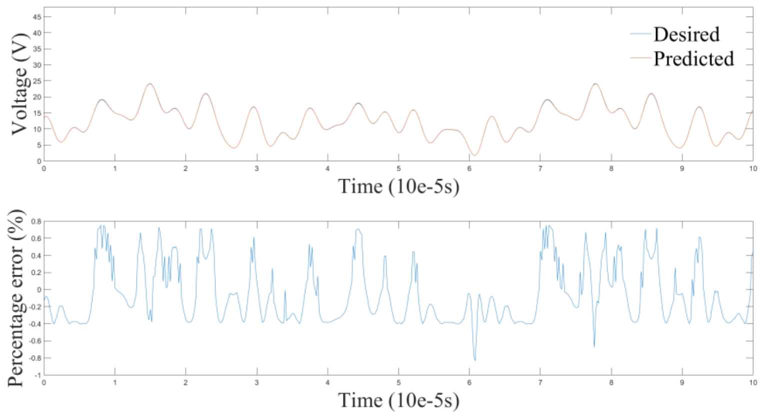

Figure 11. The upper diagram demonstrates the fitting of desired voltage output curve and the actual voltage output curve made by prediction of the FNN model.The lower diagram shows the percentage error variation over time between the desired and the actual voltage output.

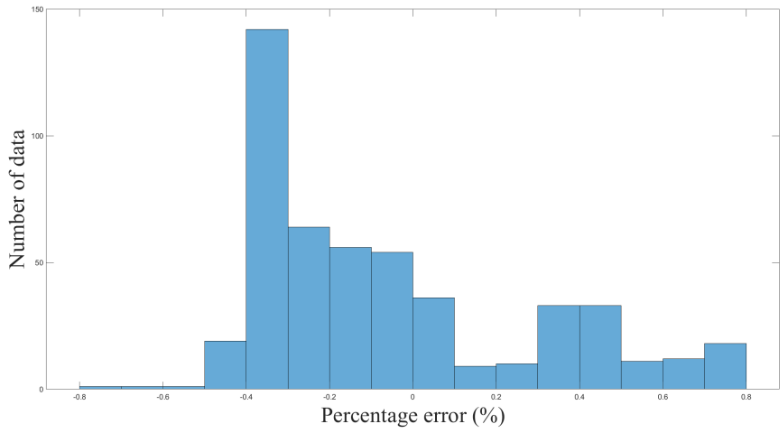

Figure 12. The error histogram of alternating voltage output simulation shown in fig.11. The desired and actual output voltage and compared to obtain a percentage error for each pair of values.

DOI: 10.54254/2753-8818/39/20240591

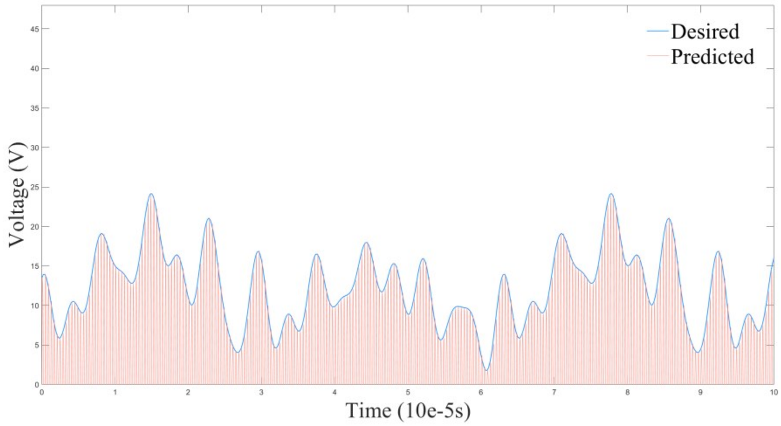

Figure 13. The diagram demonstrating envelope tracking process with values provided by the prediction made by the trained FNN model.

As shown in fig. 13, the prediction made by the FNN model is eventually used to fulfill the goal of envelope tracking. Through construction of output voltage through continuous change in duty cycle of the buck converter, the actual output voltage would fit the required output voltage to reduce energy loss.

The relationship between output voltage, output resistance and output power obeys the following equation:

$$P_{out} = \frac{V_{out}^2}{R_{out}} \tag{17}$$

Therefore, by comparing the area under the actual voltage output with the area under a consistent original voltage of 48V, which represents the ratio between energy consumed after and before envelope tracking is utilized, the envelope tracking method can save about 59.92% of original energy consumption under this particular simulation condition.

6. Conclusions

This paper presents the theory, methods, and software implementation of an envelope tracking method that can be utilized in 5G base station. This method utilized the benefits of machine learning model to make practical predictions based on large number of circuit simulation results compared with traditional prediction method based on relationship between quantities only. Buck converter is chosen as the main focus of the paper as it is more commonly used in electronic devices and the parameter that affect relationship between input and output voltage, which is the duty cycle of MOSFET in the circuit, can be easily adjusted to satisfy the need of 5G base station that requires frequent change in output voltage. By using MATLAB as the data acquisition system, large quantity of training data can be generated in small amount of time and can be processed and normalized automatically to fit the training need of the machine learning model. A large training data set as reference also ensures the precision of the machine learning model. The utilization of FNN provides shorter training cost which allows a larger training data set being imported to improve its prediction accuracy. Besides, being a one-direction neural network model, its quick-response ability ensures it to process considerable amount of inputs in short periods, which can match the need of 5G base station that requires frequent change in output voltage.

References

[1] P. F. Miaja, M. Rodriguez,A. Rodriguez,and J. Sebastian, "A linear assisted dc/dc converter for envelope tracking and envelope elimination and restoration applications," *IEEE Transactions on Power Electronics*, vol. 27, no. 7, pp. 3302-3309,2012.

DOI: 10.54254/2753-8818/39/20240591

[2] M. Liao, H. Li, P. Wang, Y. Chen, and M. Chen, "Machine learning methods for power flow control of multi-active-bridge converters, "in *2021 IEEE 22nd Workshop on Control and Modelling of Power Electronics(COMPEL)*, 2021, pp. 1-7.

[3] M. Liao, H. Li, P. Wang, T. Sen, Y. Chen, and M. Chen, "Machine learning methods for feedforward power flow control of multi-active-bridge converters, "*IEEE Transactions on Power Electronics*, vol. 38, no. 2, Pp. 1692-1707, 2023.

[4] V. Shirmohammadli, A. Saberkari, H. Martinez-Garcia, and E. Alarcon-Cot, "Integrated power management system based on efficient ldo-assisted dcldc buck converter, "in 2016 *IEEE 14th International Conference onIndustrial Informatics (INDIN)*, 2016, Pp. 282-285.

[5] M. Daryaei, S. A. Khajehoddin, J. Mashreghi, and K. K. Afridi, "A new approach to steady-state modeling, analysis, and design of powerconverters," *IEEE Transactions on Power Electronics*, vol. 36, no. 11, pp. 12746-12768, 2021.