**a)  Tone down the claims that this work (or artificial neural networks in general) achieves performance that is equivalent to human cognition or intelligence, although that may be the long-term vision.**

I have modified the following over-claimed sentences:

Abstract:

Line 1, Page 10.

NE has led to the development of biologically-inspired computer architectures ~~which may~~ whose long-term goal is to approach the performance of the human brain in terms of energy efficiency and cognitive capabilities.

Chapter 1:

Middle paragraph, Page 23

STDP as a learning mechanism based on biological observations has been ~~theoretically proved~~ implemented to be equivalent to a stochastic version of powerful machine learning algorithms.

Bottom of Page 24

NE has led to the development of biologically-inspired computer architectures ~~which may~~ whose long-term goal is to approach the performance of the human brain in terms of energy efficiency and cognitive capabilities.

Chapter 3:

Section 3.1, Page 51

Deep Learning ~~seems to have~~ has become the answer to ~~all~~ increasing number of artificial intelligence problems ~~overnight since Geoffrey Hinton~~ since Hinton et al. [2006] firstly proposed the training method of ~~a type of ANN,~~ the Deep Belief Network, ~~in 2006 [Hinton et al., 2006]~~.

**b)  Include a section on the problems to be solved for spiking networks to be able to learn continuously in practice, e.g. controlling learning, protecting memories (e.g. Grossberg’s stability-plasticity dilemma), segmentation.**

Chapter 5

Section 5.1, Page 100

I add a paragraph to state the ‘on-line’ and ‘off-line’ learning in the field of Neuromorphic Engineering. Thus, readers from various background could have a clearer and unified definition of ‘on-line’ system in the context of this thesis.I added a paragraph to state the ‘on-line’ and ‘off-line’ learning in the field of Neuromorphic Engineering. Thus, readers from various background could have a clearer and unified definition of ‘on-line’ system in the context of this thesis.

Researchers in neuromorphic engineering seem to take the term ‘on-line training’ for granted [Neil, 2013; Neftci et al., 2013] without describing it clearly. The on-line approach exploits biologically-plausible learning rules, e.g. Spike-Timing-Dependent Plasticity (STDP). Therefore, the modulation of the synaptic weights is event-driven by the spikes and operates in biological real time. On the contrary, ‘off-line’ training usually takes place on an equivalent ANN and the network parameters are tuned using traditional algorithm, e.g. gradient descent.

Middle paragraph, Page 101

Then, I include a new paragraph of the stability-plasticity dilemma in artificial systems after stating the brain is a natural on-line system:

One of the practical problems, the stability-plasticity dilemma [Grossberg, 1987] , is a typical example which only exists in artificial systems but not in the brain. Off-line trained systems cannot learn anything new, whereas on-line learning systems easily lose their previous knowledge. However, the brain intuitively achieves both stability and plasticity simultaneously; it maintains gained knowledge while being plastic in respond to new input. Hence, there will be important lessons, such as controlling learning, protecting memories/memory segmentation, and etc., to learn from the brain before an on-line SNN system delivers genuine learning capability. - Middle paragraph, Page 101

**c)  There are a large number of acronyms in the thesis. Although they are defined on first use, a table including them all is necessary.**

I add a list of acronyms before Chapter 1, Page 14-16.

**d)  Use consistent symbols in the equations throughout the thesis, which should also be defined in another table.**

I add a list of mathematical symbols before Chapter 1, Page 17-20.

**e)  P63 fig 4.2 and other similar figures should be replotted to make the distinction between the various lines clearer. A clearer explanation of what these plots show is also needed.**

I modify Figures 4.2, 4.3, 4.5, 4.7, 4.8, 4.9. 4.13, 4.15 with bolder lines in colour and increased image sizes to show a clearer distinction between the curves. I also add text to better explain the figures in the context, Page 72-84, and modify the captions of the figures.

**f)  A clearer explanation of how and where the offset term which effectively replaced the learnable biases used artificial networks is needed.**

Chapter 2

- Middle paragraph, page 39.

First of all, I explain why the biases of neurons in artificial neural network are not necessary for the task of MNIST.

Usually, a bias is included in the weighted summation which ~~can be seen as an extra input xb = 1 with its weight set to b~~ increases the expression ability of a neuron. However, in this thesis we ~~exclude biases for both artificial and spiking neurons~~ remove biases of both ANNs and SNNs to simplify the neural models and to reduce the number of parameters. Nevertheless, our experimental results show that the network using unbiased neurons performs the same when it is used to solve a relatively simple task, the MNIST.

Chapter 4

Secondly, instead of hard-coding the current bias to 0.1 (i\_offset=0.1 nA for all the LIF neurons, in the original Table 4.1, Page 73), I include the current bias *b* as a third parameter of NSP (k, b, S) to fit practical LIF firing rates. By setting i\_offset to 0, we can clearly see the curves of LIF simulation is a shifted and scaled NSP in Figure 4.7, Page 81. Consequently, there are a few places to modify in the Chapter:

1. All the LIF simulations are retested using i\_offset=0, so the Figures 4.2, 4.3, 4.5, 4.7, 4.9 are all shifted on the x-axis, Page 72-84.
2. Section 4.4.1, Page 82-83, is rewritten to describe the curve-fitting of the parameters (k, b, S) of NSP to practical LIF response firing rates.
3. The result, Page 90-92, Section 4.5.2 and Figure 4.12 show better fitting of NSP to LIF response activities, since *b* is also included for parameter fitting.

**g)  Learning in the spiking network needs to be more clearly explained – it is not clear exactly which parameter is learnt in the final implementation.**

Chapter 4, Page 88

Regarding the off-line training method, I add one paragraph:

As stated in Section 3.2, the Backpropagation algorithm updates weights using the optimisation method, stochastic gradient descent, to minimise error between the labels and the predictions from the network.

Chapter 5, Page 100:

In another word, the final learning algorithm is implemented by constructing the STDP rule and setting proper parameters: the time window τdur, the learning rates ηs+ and ηs−; and during training, the weights between any two connected neuron will be continually modified when synchronous spikes occur.

**h)  The transformations for achieving the PAF need to be explained more clearly (p72)**

Chapter 4

I modify the Section 4.4.2 mainly from Page 85-87, to better explain the figures, annotate the parameters and claim the transformation process more clearly.

**i)  The transformations between the activation function and firing rates need to be explained more carefully so that it is clear how the firing rates are kept within reasonable bounds.**

Chapter 4, bottom paragraph, Page 87

I add one paragraph in Page 80 to explain the transformation from numerical values to firing rates.

It is also significant to transform numerical values of training and testing data to firing rates in the first/last layer of the SNN. In order to keep the firing rate in a valid range of an LIF neuron, e.g. less than the maximum firing rates of λmax = 1/τrefrac, we can scale the labelling data of the last layer by multiplying λmax/S during training. Thus according to PAF (Equation 4.14), the maximum firing rate of such an output neuron would be 1 ∗ λmax/S ∗ S = λmax. We can certainly choose a much lower rate of λmax, say 200 Hz, to keep the NSP fit to the actual LIF response activities better, since the parameters of PAF are curve-fitted to a limit working range of output firing rates. For the input layer, it is the easiest to keep the original abstract values as x; then in the SNN test, we divide x by τsyn to get the input firing rates of Poisson spike trains, see Equation 4.13. But, it is also flexible to linearly map the numerical values to a range of firing rates by multiplying K Hz. Then, we use x × K × τsyn as the new input of the training network; and x × K as firing rates of spike trains in SNN testing.

**j)  P93 and related figures: precisely what the goal of this series of simulations is, what the data is, how to read the plots, etc should be explained. The use of the term ‘images’ is misleading.**

Chapter 5, Page 108

The goal of the simulations is stated in the first paragraph of the Section 5.4.

This section attempts to verify the SRM method in practice, thus we compare the learning performance of the conventional Deep Learning models to their spiking versions. We record the reconstruction performance of the models, and carefully observe the dynamics of weights modifications, the activities of the hidden and output neurons and the reconstruction loss.

Page 108-111

The data is described in Section 5.4.1 more clearly, including how to read the data inputs shown in Figure 5.5.

The term of ‘image’ is better explained:

thus providing an accurate comparison of the weight updates. The input ~~vector~~ data vector of ten dimensions, seen as an image, repeatedly fed into the network 5,000 times during training. Representing a data vector with the term ‘image’ helps us to better demonstrate the reconstruction task, and to have a unified expression as images in the MNIST dataset for later use.

**k)  In chapter 6 make it clear what your contributions were as this was a team effort.**

Chapter 6, In Section 6.3 and the conclusion, I declare the work done by other people and the contribution I made: bottom, Page 148; top, Page 149; and bottom paragraph Page 167.

**l)  Please see both copies of the thesis which the examiners have annotated for further minor points of corrections**

I have finished all the corrections annotated on the copies of the thesis.