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ENGR4450 Aplied Artifical Inteligence
Homework 2 Report

1. FFNN Prediction of SoC and SoH

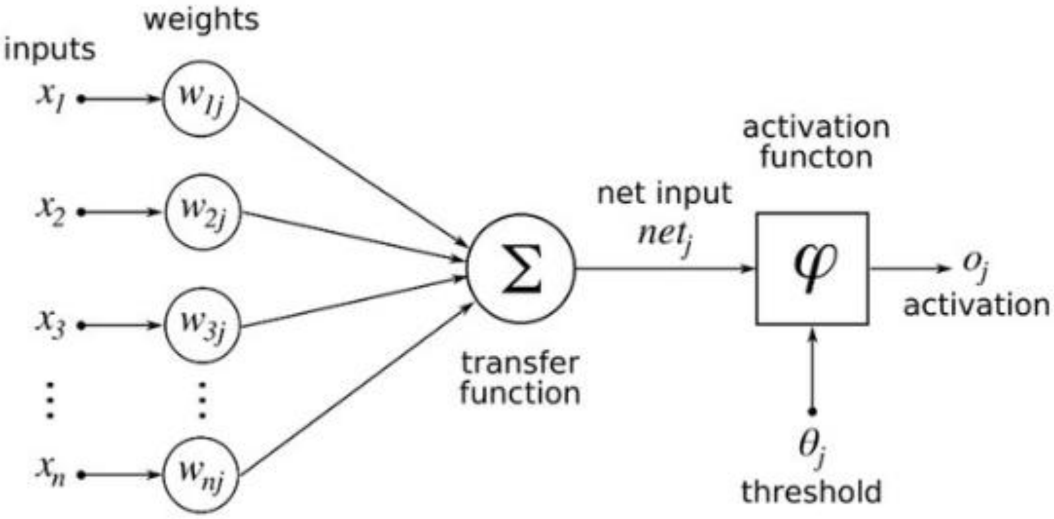


Figure 1. Structure of a single neuron in a feedforward neural network [1]

Artificial Neural Networks (ANNs) have become essential tools for solving complex problems in pattern recognition and machine learning. Among the most fundamental architectures is the Feedforward Neural Network (FFNN), which is widely used in supervised learning tasks such as classification, regression, and function approximation.

A Feedforward Neural Network is composed of layers of interconnected neurons, where data flows in one direction only: from the input layer, through one or more hidden layers, and finally to the output layer. Unlike recurrent neural networks, FFNNs do not contain feedback loops or cycles, which makes their structure simple and efficient for forward data propagation.

The diagram above illustrates the inner workings of a single neuron within an FFNN. Each neuron receives multiple input values, labeled as x1, x2, ..., xn. Each input is multiplied by an associated weight, denoted w1j, w2j, ..., wnj. These weighted inputs are summed to produce a value known as the net input (net j). This can be written as:

net j = (x1 * w1j) + (x2 * w2j) + ... + (xn * wnj)

Optionally, a threshold value (theta j) may be subtracted from this sum to regulate neuron activation. The resulting value is then passed through an activation function, such as the sigmoid or ReLU function, which determines whether the neuron "fires" and produces an output. This output is then transmitted to the next layer of the network or used as a final result.

Thanks to its feedforward structure and the ability to adjust weights during training, the FFNN is capable of learning from data and making accurate predictions. These features make FFNNs a foundational model in the fields of artificial intelligence and deep learning.

Yapay Sinir Ağları (Artificial Neural Networks – ANN), karmaşık desen tanıma ve makine öğrenmesi problemlerinin çözümünde güçlü araçlar olarak öne çıkmaktadır. Bu yapılar arasında en temel ve yaygın kullanılan mimarilerden biri İleri Beslemeli Sinir Ağı (Feedforward Neural Network – FFNN) olup, sınıflandırma, regresyon ve fonksiyon yaklaşımı gibi denetimli öğrenme görevlerinde etkin şekilde kullanılmaktadır.

İleri beslemeli sinir ağları, birbirine bağlı nöron katmanlarından oluşur ve veri akışı tek yönlüdür: giriş katmanından başlayarak bir veya birden fazla gizli katman üzerinden geçerek çıkış katmanına ulaşır. Geri besleme ya da döngü içermediğinden, yapısı sade ve veri iletimi açısından etkilidir.

Yukarıda verilen görsel, FFNN yapısı içindeki tek bir nöronun nasıl çalıştığını göstermektedir. Her bir nöron, x1, x2, ..., xn şeklinde ifade edilen birden fazla girdi alır. Bu girdilerin her biri, w1j, w2j, ..., wnj şeklinde gösterilen ağırlıklarla çarpılır. Ardından bu değerler toplanarak net giriş değeri (net j) elde edilir. Bu hesaplama, genellikle şu şekilde ifade edilir:

$$\mathbf{net\ j = (x1\ x\ w1j) + (x2\ x\ w2j) + ... + (xn\ x\ wnj)}$$

veya daha genel olarak, tüm girişlerin ağırlıklarıyla çarpılıp toplanmasıyla elde edilir.

Bu net girişten, varsa bir eşik değeri (theta j) çıkarılır. Elde edilen sonuç, aktivasyon fonksiyonu adı verilen ve genellikle doğrusal olmayan bir işlevden geçirilir. Bu fonksiyon (örneğin sigmoid ya da ReLU gibi), nöronun çıktısını belirler. Elde edilen çıktı, bir sonraki katmana aktarılır ya da çıkış olarak kullanılır.

İleri beslemeli yapısı ve eğitim sırasında ağırlıkların ayarlanabilmesi sayesinde FFNN’ler veriden öğrenme yeteneğine sahiptir ve doğru tahminlerde bulunabilir. Bu özellikleriyle FFNN'ler, yapay zekâ ve derin öğrenme uygulamalarında temel bir yapı taşıdır.

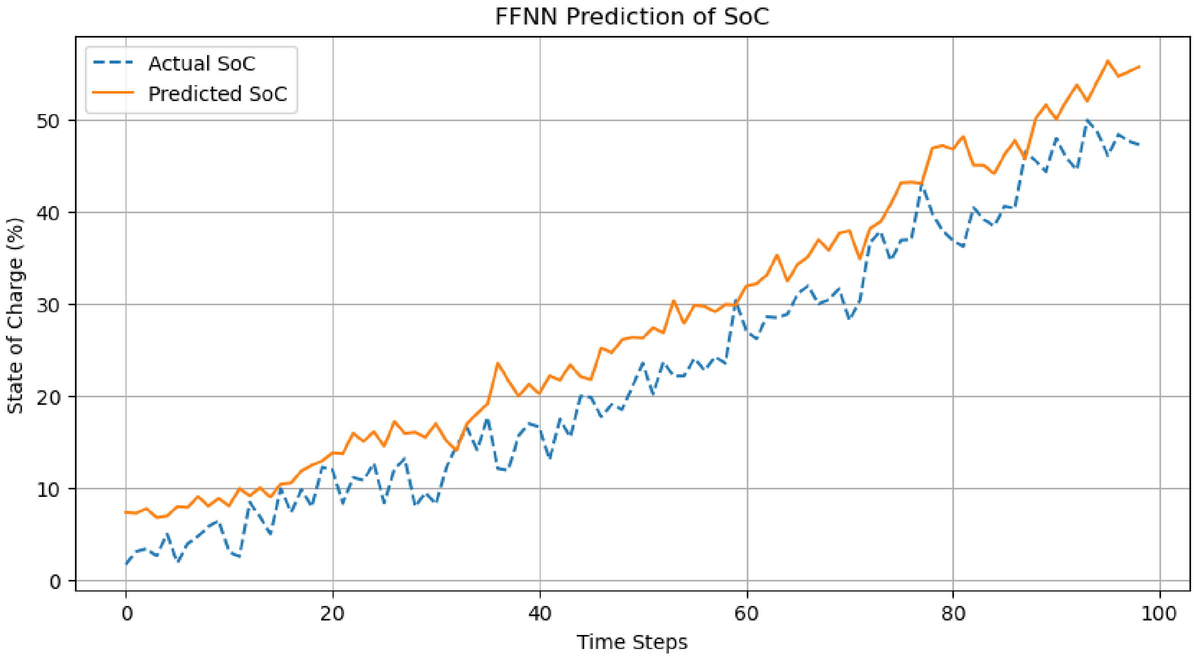
1.1 Engineering Context of the Code

Here, SoC (State of Charge) indicates how full the battery is, expressed as apercentage. In the automotive domain, it's a critical parameter for vehicle range, instantaneous performance, and energy management.

SoH (State of Health) shows the battery's aging/capacity loss condition. It decreases over time with charge-discharge cycles. It is important for long battery life and safe driving.

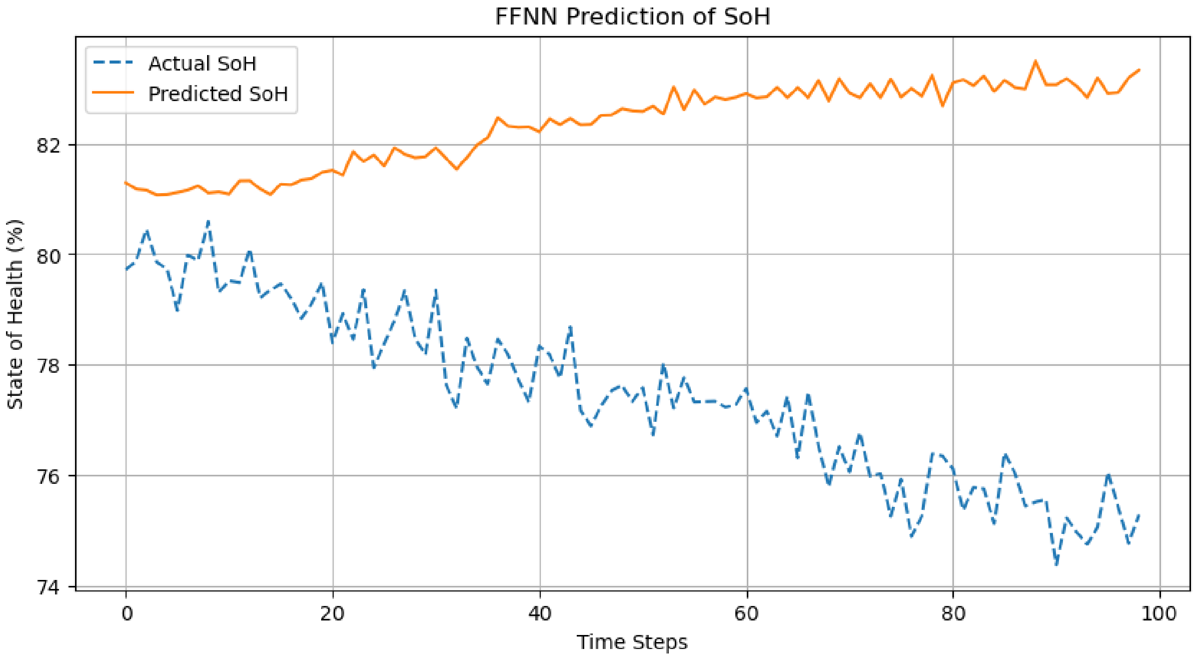
1.2 Prediction Graphs

In the graph, the orange line is “Predicted” (the model's forecast), and the blue dashed line is “Actual” (the real value).



***Graph 1**: Actual vs Predicted SoC Graphic [2]*

In the graph 1, the model captures the sine wave's fluctuation trend, but there are occasional discrepancies (especially at peaks and troughs).



***Graph 2**: Actual vs Predicted SoH Graphic [2]*

In the graph 2, the model predicts a higher tendency (around 85–88), whereas the actual value goes down to the 80–75 range. The model might be overestimating (bias).

1.3 Erol and Improvement Methods

Even though the MSE loss decreases, it may not be a perfect fit. One could try longer training, different numbers of layers, or different hyperparameters.

The dropout rate could be increased or decreased.

Other activation functions (for example, using Leaky ReLU instead of ReLU) could be tested.

1.4 Connection to Automotive Dynamics

Essentially, estimating SoC and SoH is critical for electric powertrains in EVs or hybrids, as it affects range management and battery power.

If the battery SoH is low, the vehicle could experience reduced torque distribution or less efficient regenerative braking on long drives, partially impacting the “friction circle” dynamics. For instance, if the motor power is insufficient, torque vectoring in a turn may not be as effective.

Also, as SoC decreases, less support is available from electric braking, forcing the vehicle to rely more on mechanical brakes, which in turn can affect tire-road friction differently.

REFERENCES

[1] Leong, Y. K., Chang, C.-K., Arumugasamy, S. K., Lan, J. C.-W., Loh, H.-S., Muhammad, D., & Show, P. L. (2018). Statistical design of experimental and bootstrap neural network modelling approach for thermoseparating aqueous two-phase extraction of polyhydroxyalkanoates. *Polymers, 10*(2), 132. https://doi.org/10.3390/polym10020132

[2] Laçin, G. (2025, March 28). *hw2_FFNN.ipynb* [Jupyter Notebook]. GitHub. https://github.com/gokhanlcn/AIexercises/blob/main/hw2_FFNN.ipynb