International Journal of Engineering & Technology, *7 (3.4) (2018)* 167-173

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Artificial Neural Network Model Adopting Combinatorial Inhibition Process in Multiple Solution Problems

K. Shyamala[1], P. Chanthini[2*], R. Krishnan[3], A. Murugan[4]

[1]Associate Professor, [2]Research Scholar, [3]Research Scholar, [4]Associate Professor, PG & Research Department of Computer Science, Dr.Ambedkar Government Arts College (Autonomous), Affiliated to University of Madras, Chennai, India.
**Corresponding author E-mail*: chanthini19@gmail.com

Abstract

Exploration of Artificial Neural Network (ANN) research continually opens rooms for improvement and implementation of mathematical models to solve various problems. This research work was not only to direct on the objective of problem-solving, instead the goal is to mimic basic biological functions of the brain in problem-solving situations. The basic biological theories of "Selection", "Combination" and "Inhibition" were successfully implemented in the earlier works. This work conceived another biological theory named "Sequential Firing" of neuron in solving complex problems like sum-of-subset problems. The non-modular combinatorial inhibition neural model has been proposed and implemented successfully using the time delayed sequential firing between neurons. As per the biological theories knowledge representation is a preliminary phase of learning. This work not only illustrates the sequential process of firing between neurons, it paves the way to utilize this neural model for the learning process.

Keywords: *Combinatorics, Inhibition, Non-Modular neural network, Selection, Sequential Firing*

1. Introduction

The earlier artificial neural models which effectively solve different problems by having problem solving only as their primary objective but kept mimicking the activities like that of a human brain at a distance. It will be appropriate to say that this hypothesis was conceived after initial probing of new biological theories which would help in mimicking the brain. The hypotheses conceived in this research work are,

- First, problem-solving is not only an objective of this research work. The goal is to identify and mimic the various approaches followed by the brain to solve problems.
- Second, everything is not put into the brain and got back rather there is something ready-made and can be got by proper activation.
- The third is learning which should be an external layer which may have knowledge representation as the preliminary phase of learning.

The evolution of the hypothesis started from the previous work [1] generic neural network "Selection" model to solve multiple unipolar problems. This was because of the intuition that there must be some physical commonness which adapts to environmental inputs. The generic model was implemented as the basic static circuits for the "Selection" one of the basic biological theories. This was successfully achieved by imitating biological neuron function and to provide the virtual model of a neural system which is generic, physically static and functionally dynamic one following the selection theory of G. M. Edleman [2]. Fully connected feed-forward network was found suitable for [1] the first portion (i.e.) static portion of the network and the partially connected network was suitable for the dynamic portion of the network which is functionally dynamic according to the problem situation. The dynamic portion processes in the way that one-time learning or knowledge representation for the basic unipolar problems. This representation was considered to be a preliminary phase of learning. In 2017, the "Selection" model was utilized to solve optimization problems like 0/1 Knapsack (KP) problems[3]. The second basic biological theory called "Combination" was also adopted to solve the optimization problem.

In the work [4], the selection model which was used to solve optimization problems like KP[3] was adopted to solve multiple solution problem of sum-of-subset problem. In the work [4] apart from the basic biological theories "selection" the further theories of inhibition and combinatorial functioning were included.The network was designed to perform an exhaustive search in the way that it producesmultiple outputs rather than only an optimum. Then utilization of inhibition as an integral function which eliminates some of the unwanted inputs and reduces the exhaustive search was introduced. It was identified through biological studies that "Inhibition" was an independent process which stores negative responses and acts accordingly. The successful implementation shows that negative responses are stored using short-term memory and to inhibit some inputs which will be compulsorily producing unsatisfactory results.

Copyright © 2018 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

1.1 Iterative Learning and Recursive Decision Making

Existing neural models were purely mathematical models which had the objective as learning through iteratively training the network. Even though learning is iterative, the decision making in those networks were performedas a single threaded process. Once the process for training is decided, the iteration was repeatedwith the chosen data set representing only a particular situation of the problem. This iterative process repeats until the network converges or iterates up to the specific number of epochs. This work is not a contradiction to the existing iterative learning process. This works only explores biological theories to categorize learning into multiple phases called representation and learning. This work only concentrates to find model for representation which may facilitate effective learning in future.

This research work directs to process on recursive decision making which has the process as iterative and produce the cumulative result as its decision. It is from a different perceptionto the concept of decision making through iterative learning. In 2008,the researchers from medicine have given that decision making is one of the central emerging theme in neuroscience which has a recurrentdecision-making process [5][6]. The study of cognitive behavior says that decision-making mechanism depends on "slow recurrent synaptic excitation balanced by fast feed-forward inhibition".

These works which provided promotions towards the set objectivity of finding a virtual implementation for biological theories have also left various questions to be answered similar to that of biological endeavors. This work was decided to provide implementations of proven biological theories and not to provide new questions to the aspirants in biology.

1.2 Classical Nature of Inhibitory Neurons

Inhibition similar to consciousness falls into the domain of philosophy as a process which may be the subject matter for study in empirical sciences. The inhibition which was considered as a process in earlier stages, through modern studies in biological is now getting identified with neural networks of different locus of our brain. It was necessary for this work to find the proper network model which includes the neural representations for the process of inhibition. A major portion of the current work was not to hypothesize a network model which will imitate the inhibition as a process; in contrast it was to get a right accumulation of proven facts about inhibitory neurons which would pave the way to provide a virtual model for such identified biological networks. This was achieved in an incremental fashion. The first part of this work happened by giving improvement through a data structure approach to the algorithm used in the previous work [4]. The later portion of this work is provided through a suitable network model for the same. This was done and tested by formulating a neural network model for the sum-of-subset problem.

The previous work [4] illustrated the successof introducing the theoretical contemplation of "Inhibition a process" into virtual model implemented to the problems with multiple outputs. Even though the algorithm was an improvement to the earlier model devoid of such algorithm, the quantum of imitation achieved to the biological network was not satisfactory. The objective of the algorithm was to reduce the process of summation to the inputs which include the pattern of inputs which have already produced negative results. The algorithm used the method of removing such future inputs from the set of probable inputs by comparing each and every one of them exhaustively with the inputs which produce a negative response or the decried sum. The algorithm left gaps for improvements in two accounts, the first was the reduction of complexity of exhaustive search for elimination and the second to improve quantum of imitation of the biological model by not eliminating the probable inputs rather consider it and curtails summation process only.

2. Related Work

In 1997 D.Elizondo et al.[7] have done the study on partially connected neural networks in the way that produces the improved performance than the fully connected neural network. The reduction in connectivity reduces the complexity and lead to improving generalization in the network with reduced storage requirements. When the connection complexity is reduced then the number of weights needed for the network also gets decreased. The works [8-10], shows the successful implementation of weight sharing strategy through the partially connected neural network. It was achieved by sharing a single weight between the two or more connection in the network. The authors from this work [11][12] has concluded that partially connected network (i.e.) locally connected model achieves good performance level when compared with fully connected neural network (i.e.) globally connected models. In the works [13][14] the authors demonstrate the dynamic neural model with single neuron calculation. The single neuron depicts as input delay which represents the three delay elements by the single operator (D). The Input Delay Neural Network(IDNN) was designed and the process of a single neuron (i.e.) time delay was designed as an internal structure of the architecture. The time delay was considered as tapped delay line (P) that involves between the inputs to hidden neuron for most recent inputs. After successful implementation of IDDN, the authors suggested that this network also be applicable for time step input delay related problems.

In 2015, Min-Suk Kang et al.[15] discussed the concept of memory retrieval of mutual inhibition in motion stimulus. Their experimental analysis shows that memory retrieval of motion stimulus inhibits the competing representations still held in short-term memory. In 2007, James M. Tepper et.al [16] have established the presence of inhibitory feedback circuits in neostriatalGABAergic spiny neurons. The emphasis of the findings that the abundance of inhibitory synapses in the feedback circuits more than that of feedforward circuits was a driving factor for the design of the current virtual model. The current model is designed to imitate the findings of the work [16] that feedback systems functions at the areas of dendrites for regulating local processes.

3. Objectives

The goal of this work is to achieve the following objectives,

- The main objective of this work is to provide a virtual model for process of inhibition as an integral part of a non-modular neural representation.
- To implement the virtual model using sum-of-subset problem which should be with the complete combinatorial inhibition in reducing the probable inputs that will produce an unsatisfactory result predicted through the combinational inter relationship.

4. Neural Representation of Process of Inhibition

Like consciousness,the process of inhibition is an accepted concept in psychology. The empirical studies in biology have categorized the effect of some neurons to their post synaptic ones are inhibitory in nature. The current work having the objective of providing virtual models only to proven theories in biology needed strong support from biological endeavors to provide support for a virtual model for inhibition through the findings of neural representations for the process of inhibition. These studies have also proven that a neural representation being permanent, executes a dynamic inhibitory process with the help of short-term memories of the no-go conditions of the problem situation. Lateral inhibition is a widely analyzed topic in biology has it the mechanism widely identified to be used by the brain in decision making for complex problems.

4.1 Implementation

The previous work [17] shows the successful implementation of the proposed data structure Combinatorial Inhibition Graph (CIG) to optimize the process of inhibition. The results elucidate the improved performance of multiple solution problems namely sum-of-subset over exhaustive search elimination method which pavesthe way to create a non-modular neural representation for the process of inhibition. The present work shows the successful implementation of the sum-of-subset problem by considering combinatorial and inhibition as a portion of the neural system. Figure 1 elucidates the complete working process of combinatorial inhibition process for the sum-of-subset problem. It shows the working model of the non-modular neural representation of combinatorial inhibition neural system. Later each portion of the network is demonstrated along with the complete neural architecture.

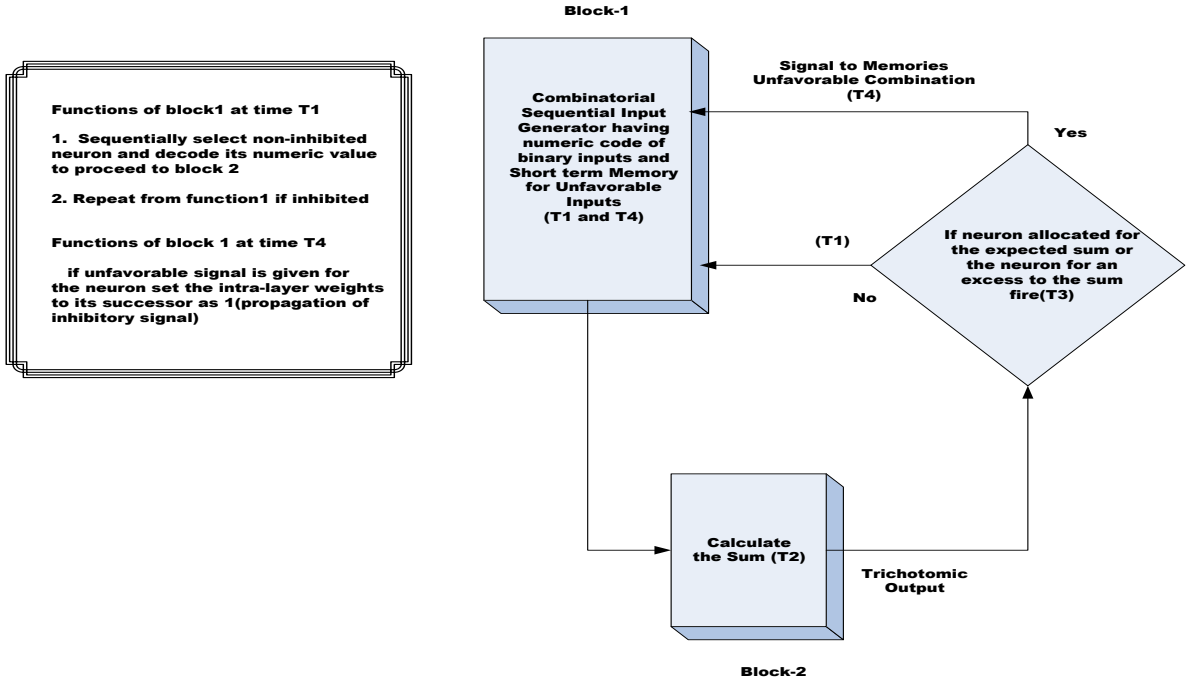


Fig.1: Non-modular Neural representation for the process of combinatorial inhibition process

4.2 Block-1 Description

To demonstrate the combinatorial inhibition process, the neurons are arranged systematically with intra-layer connections. Figure 2 shows the systematic arrangement of a single layer of neurons with intra-layer communication to depict the combinatorics and functional relationship between them. Each neuron has the numeric code of the binary input and a binary short-term memory to represent the inhibition status of the particular code.According to the combinatorial optimization principle [17], if a basic combination exceeds or equal to the desired sum then further matching combinations are eliminated for summation process i.e. according to the biological theory set into an inhibited state. From Figure 2 neurons are initiated and sequentially select the non-inhibited neuron to proceed at time T1. By default the weights between the intra-layer neurons are 0. When unfavorable signal is given for the neuron then,the intra-layer weights to its successor are set as 1 for propagation of inhibitory signal. The mathematical representation for the propagation of inhibitory signal is given as in (1).

$$IS_i^{n+1} = \sum Wt_{ji} IS_i^n \;\; where\; j = n - (n - nob) \qquad (1)$$

Where, IS represents inhibitory status, Wt represents weights between intra-layer neurons and ‘nob’ represents number of high bits in the binary code.

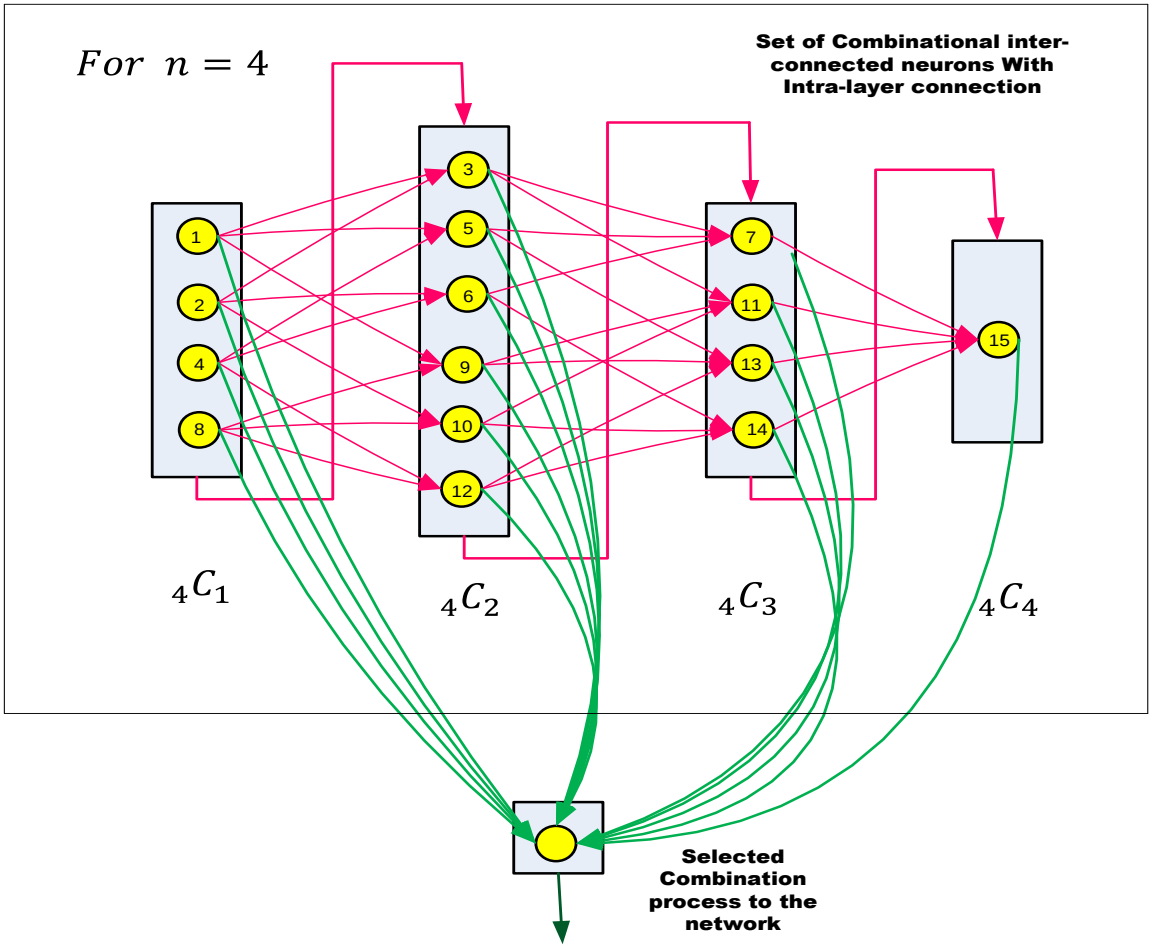


Fig.2: Neural Representation of Process of Inhibition

The previously implemented CIG algorithm [17] identifies all its neighbors (i.e.) related combinations at each level, which gave someset ofrelated combination recursively so that condition checking is done repeatedly. In case of the neural representation of combinatorics, the intra-layer connection Figure 2 illustrates the functional adaptation to the neural network which eliminates redundant processing. When comparing with CIG [17], the non-modular neural representation of "process of inhibition" eliminates the redundant processing in identifying related combination and propagating inhibition signal.

4.3 Block-2 Description

The network architecture of sum-of-subset is shown in Figure 3 it is adapted sum-of-subset neural model from the previous work[4]. It contains three layers: input, hidden and output layers, each layer consist of one or more neurons and the structure of network was followed by the previous work [1][3]. First portion input to first hidden is fully connected network and from first hidden layers to output is the dynamic portion that is partially connected network and connection varydepending upon the problem situations. The network was implemented with the basic biological theories namely "Selection", "Combination", "Inhibition" and "Sequential Firing". Sequential firing of neurons is the main objective of this work to implement the complex problem like a sum-of-subset problem with non-modular combinatorial inhibition as an optimization. The sequential firing is achieved by introducing a time delay between the processes. The time delay between the processes can be defined as

$T_1 \rightarrow$Sequentially select thenon-inhibited combination from Figure 2 the neural representation of process of inhibition.

$T_2 \rightarrow$ Find the summation for the selected combination

$T_3 \rightarrow$ Get the Inhibition signal.

$T_4 \rightarrow$If the response is negative, then propagate the inhibition signal by setting the intra-layer weights to the successor 1. Otherwisestart T_1.

These are the fourtime delay co-operative process which makes the firing of neuron sequentially.

Functions of non-modular network at sequential timing conditions as follows

Algorithm: Non-Modular Sequential Timing Process

1. ***Begin***

2. ***Initialize Block 1 (Figure 2), Initialize Block 2 (from [4])***
3. ***Start T1***
4. ***If inhibited then***
5. ***repeat T1***
6. ***Else***
7. ***Start T2***
8. ***Set the output (to any one of the three output neurons according to the comparison of the sum with the expected sum)***
9. ***If any neuron other than the one representing lesser than the expected sum fires***

   Start T4
10. ***End if***
11. ***End if***
12. ***End***

The first set of inputs (W) represents the weights of the given item and second set of inputs (C) represents the chosen combination. Two set of hidden layers are used, the first hidden layer imitates the inhibitory synapses which can enable or disable the activation of hidden neurons. Their functions are mathematically represented as in (2)

4.3.1 First Hidden Layer

$$S_j = (1 - IH_{zj}) * \sum_j C_i w_{ij}^{IF} + Bw_j^{FB} \quad (2)$$

Where,

$IH_{zj} \rightarrow$ the firing of z[th] neuron is used as inhibitory signal by $(1 - IH_{zj})$ form as it nullifies the post synaptic actions when fired.

$S_j \rightarrow$ the output of j[th] neuron in first hidden layer

$C_i \rightarrow$ Unipolar inputs

$w_{ij}^{IF} \rightarrow$ Static weight as per model1 [1]

$B \rightarrow$ Bias input as per model1[1]

$w_j^{FB} \rightarrow$ Bias Weight

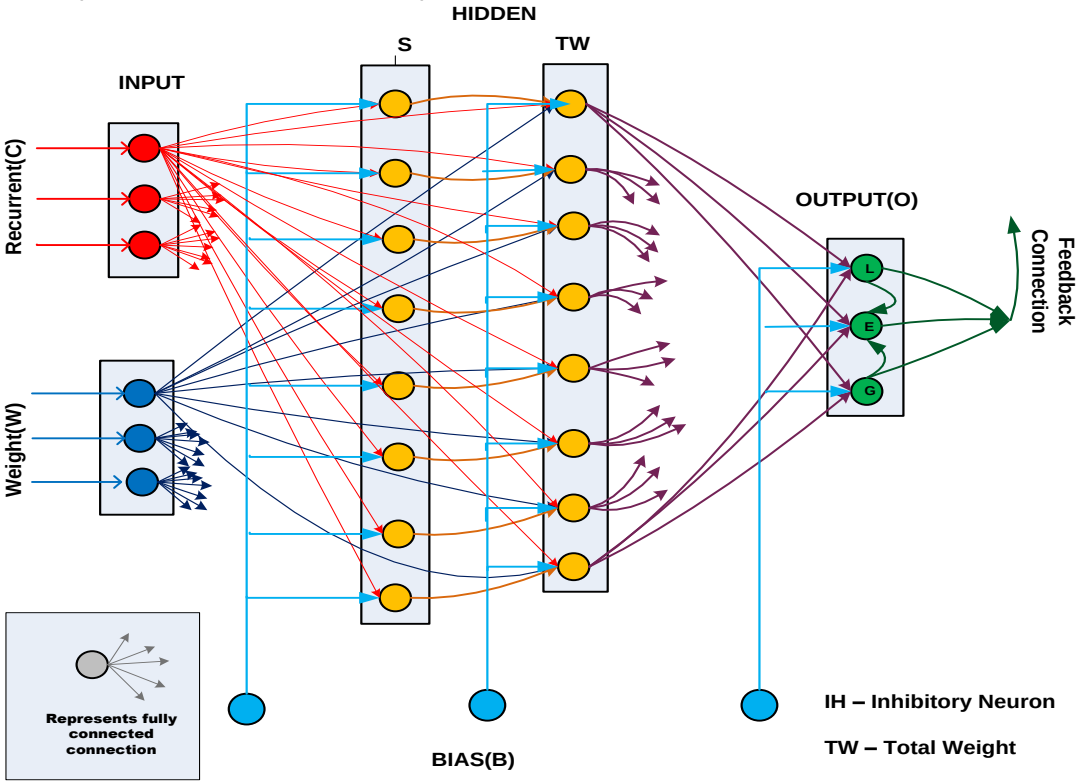


Fig.3: Sum-of-subset neural model

4.3.2 Second Hidden Layer

The second hidden layer used to find the cumulative sum for the selected items and its mathematical functional representation is given as in (3)

$$TW_j = S_j\left[\sum_j (C_i W_i \quad) * w_{ij}^{FS} + Bw_j^{SB}\right] \quad (3)$$

Where,

$TW_j \rightarrow$ Cumulative Weight

$w_{ij}^{FS} \rightarrow$ weight of the i[th] neuron in the second hidden layer

$B \rightarrow$ Bias input

$w_j^{SB} \rightarrow$ Bias Weight

4.3.3 Output Layer

The output layer is functionally dynamic it consist of three neurons each can fire according to the problem situations. The first output neuron used to fire when the summation is lesser than the desired sum. The functional representation is given as in (4).

$$L = \sum \ TW_j * \left(w_j^{SO}\right) + Bw_L^{OB} \quad (4)$$

Where,

$L \rightarrow$ The neuron which fires if the sum is Less than the desired sum.

$w_j^{SO} \rightarrow$ Staic weights of -1.

$B \rightarrow$ Bias input to the neuron L.

$w_L^{OB} \rightarrow$ Bias Weight is (TS-1), where TS is the sum of all the n elements of the given set.

The second output neuron get fires when the summation is equal to the desired sum. The functional representation is given as in (5)

$$E = (1 - L)(1 - G) \sum \ TW_j * \left(w_j^{SO}\right) + Bw_E^{OB} \quad (5)$$

Where,

$E \rightarrow$ The neuron which fires if the sum is Equal to desired sum.

$w_j^{SO} \rightarrow$ Weight of the neuron E from j[th] TW neuron.

$B_1 \rightarrow$ Bias input to the neuron E.

$w_E^{OB} \rightarrow$ Bias Weight is $TS - 2(DS)$, where TS is the sum of all the n elements of the given set.

$DS \rightarrow$ Desired Sum.

The third neuron in the output layer gets fire when the sum is greater than the desired sum. The functional representation given as in (6)

$$G = \sum \ TW_j * \left(w_j^{SO}\right) + Bw_G^{OB} \quad (6)$$

Where,

$G \rightarrow$ The neuron which fires if the sum is Greater than the desired sum.

$w_j^{SO} \rightarrow$ weight of the neuron G from j[th] TW neuron.

$B_1 \rightarrow$ Bias input to the neuron G.

$w_G^{OB} \rightarrow$ Bias Weight is $TS - 2(DS)$, where TS is the sum of all the n elements of the given set.

$DS \rightarrow$ Desired Sum.

When any second or third neuron fires, the inhibition signal is given as feedback to the combinatorial portion to propagate the inhibition signal to the successor neuron.

5. Results and Discussions

From previous works [4][17], the multiple solution problems like sum-of-subset problems are solved successfully with improved performance. In the work [4], the sum-of-subset problem was implemented and tested successfully through exhaustive search method and exhaustive search elimination method through the process of inhibition as an internal and independent process. In the work [17], new data structure Combinatorial Inhibition Graph (CIG) was proposed and successfully implemented with the efficient results.

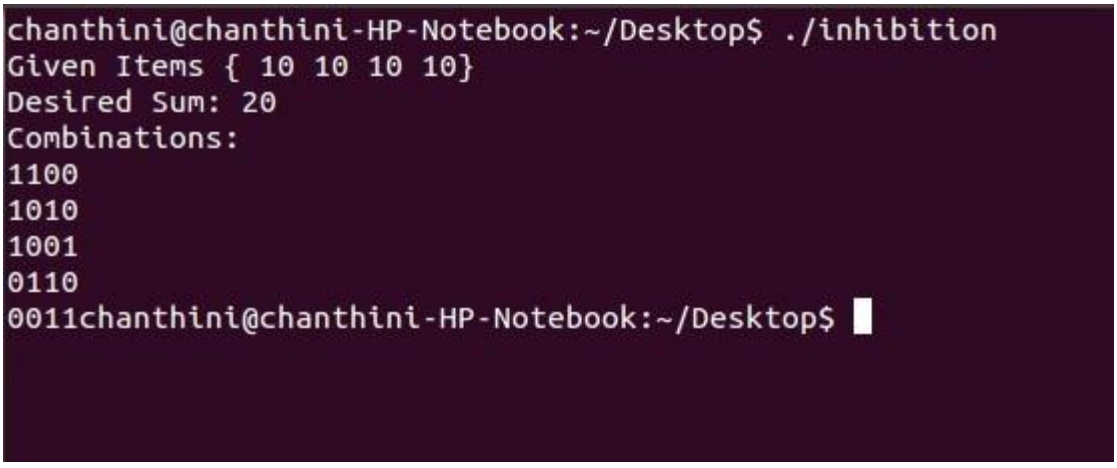


Fig.4: Sample output for sum-of-subset problem

The current works show the elimination process of exhaustive search and also eliminated recursive process from CIG for identifying related combinations through non- modular neural representation of combinatorial inhibition network. Figure 4 elucidates the successful implementation of sum-of-subset problem. The result demonstrates with the collection of four items with the desired sum and the multiple outputs suitable to the given problem.

6. Conclusion

The intuition of mixed nature of non-modular combinatorial inhibition has been proposed and implemented successfully. The sequential firing and time delay between the neurons are depicted through the solvation of multiple solution problem namely sum-of-subset. The earlier work CIG and biological probability provide the suitable implementation of thenon-modular neural system. The non-modular neural representation for the process of combinatorial inhibition depicts the elimination of process based exhaustive search and input baring mechanism using CIG algorithm. This successful implementation paves the way to utilize these basic biological virtual models to improve learning processes as further advancements. The implementation of earlier virtual neural models are considered to be a knowledge representation models this gives direction to utilize the implemented networks for learning according to the problem situations.

References

[1] Chanthini P, Shyamala K, "Neural Darwinism Inspired Implementation of an Artificial Neural Network Model," International Journal of Control Theory and Applications. Vol 10 (23), pp 7-16, 2017.

[2] Edelman, Gerald M. "Neural Darwinism: Selection and reentrant signaling in higher brain function," Neuron, vol. 10(2), pp. 115-125, Feb. 1993.

[3] Shyamala, K., Chanthini, P.: A Novel Approach in Solving 0/1 Knapsack Problem Using Neural Selection Principle. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering. Issue-III., pp. 305--309 (2017).

[4] Shyamala K, Chanthini P, "Sum-of-Subset Implementation Using Neural Selection Principle and Cognitive Process of Inhibition," has been "Accepted" in 1st International Conference on Communication, Networks & Computing (CNC – 2018), ITM University Gwalior, 22nd – 24th March 2018, Springer CCIS ("in-press").

[5] Wang, Xiao-Jing. "Decision making in recurrent neuronal circuits." Neuron 60.2 (2008): 215-234.

[6] Shenoy, Pradeep, and Angela J. Yu. "Rational decision-making in inhibitory control." Frontiers in human neuroscience5 (2011): 48.

[7] Elizondo, D., and Emile Fiesler. "A survey of partially connected neural networks." International journal of neural systems 8.05n06 (1997): 535-558.

[8] LeCun, Yann, John S. Denker, and Sara A. Solla. "Optimal brain damage." Advances in neural information processing systems. 1990.

[9] Sanger, Terence D. "Optimal unsupervised learning in a single-layer linear feedforward neural network." Neural networks 2.6 (1989): 459-473.

[10] Kung, S. Y., J. N. Hwang, and S. W. Sun. "Efficient modeling for multilayer feed-forward neural nets." Acoustics, Speech, and Signal Processing, 1988. ICASSP-88., 1988 International Conference on. IEEE, 1988.

[11] Provence, John D., and S. Naganathan. "Locally versus globally interlayer-connected feed-forward neural networks: a performance comparison." Applications of Artificial Intelligence VIII. Vol. 1293. International Society for Optics and Photonics, 1990.

[12] Redding, N. J., A. Kowalczyk, and T. Downs. "Higher order separability and minimal hidden-unit fan-in." Artificial neural networks 1 (1991): 25-30.

[13] El-Shafie, Ahmed, et al. "Dynamic versus static neural network model for rainfall forecasting at Klang River Basin, Malaysia." Hydrology and Earth System Sciences 16.4 (2012): 1151-1169.

[14] Lu, Wenlian, and Tianping Chen. "Synchronization of coupled connected neural networks with delays." IEEE Transactions on Circuits and Systems I: Regular Papers 51.12 (2004): 2491-2503.

[15] Kang, Min-Suk, and Joongrul Choi. "Retrieval-induced inhibition in short-term memory." Psychological science 26.7 (2015): 1014-1025.

[16] Tepper, James M., Charles J. Wilson, and Tibor Koós. "Feedforward and feedback inhibition in neostriatal GABAergic spiny neurons." Brain research reviews 58.2 (2008): 272-281.

[17] Shyamala, K., Chanthini,P., Krishnan,R., and A. Murugan. "Adoption of combinatorial graph for inhibitory process in optimization problems." International Journal of Applied Engineering Research (IJAER) (2018)("in-press").