ePAMeT: evolving Predictive Associative Memories for Time Series

Iman AbouHassan* [1,2], Nikola K. Kasabov* [3,4,5]
Tanmay Bankar[6], Rishabh Garg[6], Basabdatta Sen Bhattacharya[6]

1. *Technical University of Sofia, Sofia, Bulgaria.*
2. *Central Bank of Lebanon, Beirut, Lebanon.*
3. *KEDRI, SECMS, Auckland University of Technology, New Zealand.*
4. *IICT, Bulgarian Academy of Sciences, Sofia, Bulgaria.*
5. *Dalian University of Technology, Dalian, China.*
6. *BITS Pilani, Goa, India.*

**** Contact persons:***
Nikola Kasabov (nkasabov@aut.ac.nz), ORCID id: 0000-0003-4433-k7521
Iman AbouHassan (iabouhassan@tu-sofia.bg; iabouhassan@bdl.gov.lb), ORCID id: 0000-0001-5552-1311

ABSTRACT:

Associative memories (AM) are at the core of human intelligence and learning systems. While there have been some neural network AM developed for vector-based data such as images, current machine learning methods, including deep neural networks, do not allow for training a model on time series data and recalling it on a subset of variables measured over a shorter time window. They also do not support further incremental training of the model on new temporal data and new variables. This paper introduces a new framework and method for the creation of evolving predictive associative memories for time series, abbreviated here as ePAMeT. The method is based on spiking neural networks (SNN). ePAMeT introduces significant adaptability in handling time series data with reduced or newly introduced features. This model maintains high accuracy and explainability, offering substantial improvements over traditional methods in dynamic and uncertain environments. First, an SNN model is trained on multiple time series using all available variables measured at a full-time length, and then the model is recalled on subsets of variables at a shorter time measurement without compromising predictive accuracy. Using a shorter time for recall makes early prediction of events possible. The SNN model can be further adapted/evolved on new data without pre-training the model on the old data, even using new variables. This is possible due to the evolving connectivity of the SNN model. A dynamic graph is extracted from the SNN model to capture dynamic interactions between the used temporal variables at any time during the evolution of the model, which constitutes strong explainability and a generation of new knowledge. The method is illustrated on original financial time series data, but it is applicable to many other domain areas as discussed. The proposed method has advantages over traditional machine learning methods in terms of evolvability, explainability, knowledge discovery, and using partial information of both the number of variables and their time length for the recall of the model on new data. The proposed framework opens the field for creating new types of evolvable time series prediction models. Future developments are discussed.

Keywords: *Multiple time series, Predictive associative memory, Spiking neural networks, NeuCube, Evolving systems, Expainability, Financial time series, Knowledge representation.*

1. INTRODUCTION

In today's globalized world, predictive modelling of time series data is a generic problem in various fields, including finance, economics, science, technology, and engineering. Traditional methods often struggle with non-linearity and lack of evolvability on high-dimensional data. They typically require complete datasets to make accurate predictions and cannot recall models using partial or imprecise temporal variables. These methods also lack adaptability, as they cannot incorporate new variables and new data streams without comprehensive retraining, limiting their effectiveness to work on changing datasets [Song & Kasabov 2005; Kasabov 2012; Nuntalid 2011; Li 2017; Sánchez 2016; Singh & Saraswat 2017]. Modern approaches, such as deep neural networks and Transformers, have difficulties in predicting time series based on partial temporal information. That requires identifying complex patterns in spatio-temporal or temporal streaming data. Consequently, there is a pressing need for models that can handle partial information, that can evolve with new data, and provide explainable insights into the temporal relationships within the data. The challenge is how to use a large scale of available temporal data to create a machine learning model that can be recalled at different times with a smaller number of available variables, measured at shorter times, and be further adapted to new variables.

This paper introduces, for the first time, a realization of associative memory for streaming time series data (ePAMeT). This novel framework leverages SNNs to address these challenges effectively, allowing a trained system to recall using only a subset of variables and a shorter measurement period.

The proposed ePAMeT constitute a groundbreaking approach towards predictive modelling of time series and spatio-temporal data, where a system can be recalled on partial temporal and/or spatio-temporal information. The primary objectives of this study are to enhance predictive accuracy, ensure model adaptability to new data, and provide explainable insights into the relationships between temporal variables. Model adaptability means ePAMeT can incorporate new data and new variables without needing full retraining, making it suitable for dynamic environments with continuously changing data. Unlike existing models, ePAMeT can make predictions with a subset of variables measured over a shorter time window. It can also adapt to new variables without retraining on the old data. This is illustrated in the paper on financial data. The discussion part comments on other fields where such approach has not been used so far and can be used in the future.

1.1 Literature Review on Associative Memory

Associative memory (AM) is defined as the ability to learn and remember relationships between multimodal items and to recall these associations using partial information.

There are mainly two types of AM:

- Auto-associative, where patterns of data are learned and recalled from partial data of the same type;
- Hetero-associative, where patterns from different types are matched.

The human brain learns incrementally from a lot of information. It performs spatio-temporal associations between related patterns to store this knowledge in space and time robustly. This structured knowledge between events and their spatio-temporal attributes is retrieved to make predictions of future events when only part of the information is available, either due to limited sources, limited time to make the decision, or both [Kohonen 1998; Benuskova 2007]. Although AM is one of the most essential forms of human memory, the mechanisms underlying it are still unknown [Lee 2021].

Some AM models based on neural networks have been proposed in the literature. The Hopfield network [Hopfield 1982] is a special kind of recurrent neural network that can be used as AM for vector-based pattern recognition. Bi-directional AM was developed in [Kosko1988] and is also a vector-based one. Other machine learning models with features of AM have been developed, e.g. [ElSaid 2019; Maciąg 2021; López 2014; Ibad 2022; Yusuf 2017], some of them applicable to time series, but all of them considering inputs as vectors rather than whole spatio-temporal patters and neither of them being able to incrementally add new variables.

A Hetero-Associative Memory Network (HAM) using spiking neural networks proved its effectiveness in learning and recalling associations between input and output vectors [Gerstner & Hemmen 1992]. An auto-associative memory based on a spiking neural network (SNN) uses FPGA architectures' vast connection resources to mimic biological brain networks' axons [Ang 2011]. A SNN-based model is proposed in [Hu 2015]. Simulation results show that synaptic modification of connections between input layers and hidden layers allows for hetero-associative memory, and recurrent connections between hidden layers allow for auto-associative memory [Agnes 2012]. However, all these models are vector-based. They are not applicable to time series data with changing number of temporal variables and the time of their measurements.

1.2 The ePAMeT Model's Unique Contributions

A recent study [Kasabov 2023a] suggested that using brain-inspired SNN architectures is a promising direction for building AM models for brain data. This direction is explored here for the creation of the first evolving predictive associative memories for time series based on SNN, abbreviated here as ePAMeT, and the models are generic, rather than dealing with brain data only. The ePAMeT model addresses the shortcomings of existing methods by enabling predictions with subsets of variables and shorter time frames, allowing early predictions even with incomplete data. Its design supports evolving learning, adapting to new variables without retraining the model. Additionally, ePAMeT provides explainability by generating variable interaction networks that show how different temporal variables interact over time to influence predictions, making the model's outcomes more understandable and explainable.

The paper is organized as follows: Section 2 presents background information on SNN and the brain-inspired SNN architecture NeuCube [Kasabov 2014]. Section 3 introduces the proposed ePAMeT framework, which is shown in Fig.1. Section 4 presents an experimental study using the method on trading time series data, and Section 5 applies the method to a second case study of time series data of commodity prices. Section 6 is the conclusion.

2. Spiking neural networks (SNN) and the NeuCube brain-inspired SNN architecture

2.1.Spiking Neuron Models

In SNN, information is represented and processed as sequences of spikes, i.e., binary events at specified times. SNN departs from the traditional neural network learning algorithms by the fact that they can learn “time” in their connections. There are several types of spiking neurons, and SNN introduced so far [Song 2000; Tu 2017; Thorpe 1998; Kasabov 2014; Tan 2020; Kasabov 2019; Izhikevich 2006; Ikegaya 2004; Indiveri 2015]. The Leaky integrate-and-fire (LIF) neuron model is adopted in many SNN systems (for a review, see [Kasabov 2019]). It is a simple RC-circuit with a potential leakage, characterized by low computational cost. The neuron will emit a spike when the accumulated input voltage reaches a threshold and then reset to a resting state. The dynamics of the membrane potential u(t) of the neuron are shown in (1).

$$\tau_m \frac{\partial u}{\partial t} = R.I(t) - u(t) \tag{1}$$

where, R is resistance, I(t) membrane current, u(t) membrane potential, and τ_m=$R.C$ neuron's membrane time constant.

2.2.Spiking Learning Rules

Spike-Timing Dependent Plasticity (STDP)

Spike-Timing Dependent Plasticity (STDP) is a learning rule used in spiking neural networks [Song 2000], where the strength of synaptic connections is adjusted based on the precise timing of spikes between connected neurons. If a pre-synaptic neuron fires first, before a post-synaptic neuron, then long-term potentiation (LTP) is established to strengthen the synapse weight. Conversely, if a post-synaptic neuron activates first, a long-term depression (LTD) occurs, weakening the connection weight. This adjustment, which is based on the firing order, allows the network to learn and store temporal patterns as "time" becomes implicit in the SNN model.

The modification of the synaptic weights (increase or decrease) can be defined as a function of the firing times of pre-synaptic and post-synaptic neurons based on the difference between t_{pre} and t_{post}. STDP learning creates long-term memory by changing connection weights to form LTP or LTD. Once data is learned, the SNN retains the connections as long-term memory. In some SNN structures, if just part of the new information is inputted, a chain of activities would fire in the SNN based on established connections [Song 2000; Tu 2017; Thorpe 1998]. Thus, an SNN can be potentially explored for learning long spatio-temporal patterns and utilized as AM and as a predictive system for event prediction when only some initial new input data is presented.

The STDP function is defined as in (2).

$$\Delta\omega = \begin{cases} +a\,.\,e^{\frac{t_{pre}-t_{post}}{\tau_+}} & \text{if } t_{pre} < t_{post} \\ -a\,.\,e^{\frac{t_{post}-t_{pre}}{\tau_-}} & \text{if } t_{pre} > t_{post} \end{cases} \tag{2}$$

Where: Δω is the change of the weight between pre- and post- synaptic neurons, when spikes are emitted on both of them at times t_{pre} and t_{post} correspondingly; a is a positive constant learning rate.

The rank order method (RO)

The rank order (RO) method [Thorpe 1998] is a learning rule that assigns connection weights based on the order of incoming spikes across all synaptic inputs to a spiking neuron. It prioritizes the first spike received and modulates the strength of synaptic connections according to the order in which spikes arrive, allowing the network to identify and prioritize significant temporal features. RO allows for new connection weights to be formed depending on the order of the incoming spikes and the number of spikes that follow the first spike, as shown in equation (3).

$$\omega_{i,j} = \alpha.mod^{order(j,i)} \pm d\ , \tag{3}$$

Where: $\omega_{i,j}$ is the synaptic weight between a pre-synaptic neuron j and the post-synaptic neuron i; α is a learning parameter; *mod* is a modulation factor that updates the weight based on the order of the first spike occurrence at synapse j,i in relation to the order spikes arrived at the other synapses of the post-synaptic neuron i; $order(j,i)$ represents the order of the first spike at synapse j, and it is zero if this spike is the first that has arrived at neuron i across all synapses; d is a drift parameter to update the connection weight on subsequent spikes arriving after the first spike on each of the synapses of neuron i.

2.3.The NeuCube SNN Architecture

The NeuCube architecture [Kasabov 2014], also implemented as software in [HTTP NeuCube] is inspired by the human brain and its ability to learn spatio-temporal data. It learns from data and connects clusters of neurons to capture complex temporal relationships between various spatial features involved in time series data and to provide a more interpretable representation of the underlying dynamics.

The NeuCube architecture consists of modules for encoding input times series into spike sequences, unsupervised learning of spike sequences into a 3-dimensional SNNcube; supervised learning for classification or regression as outputs.

Spike encoding of input time series

The input data are spatio-temporal or temporal time series of continuous values. Several encoding algorithms have been introduced and studied so far to encode the continuous values times series into sequences of spikes (for a review, see [Kasabov 2019, Petro 2020, Kasabov 2012, Nuntalid 2011]). The choice of the encoding algorithm depends on the type of time-series data being analyzed. Threshold-based encoding (TBR) is considered the most generic and has been found suitable for the type of data used in our experiments. In the threshold-based encoding algorithm, excitatory (positive) and inhibitory (negative) spikes are generated when significant changes in the signal intensity surpass a calculated threshold (4). These spikes are created only if consecutive input variations differ from the threshold (H). The current spike threshold *H(k)* at step k, used to encode input signals into spikes at this step, is determined by the mean and standard deviation of the values of the input time series data presented to the SNN from steps 1 to k.

The effectiveness of TBR lies in its ability to filter out minor fluctuations and noise, thereby enhancing signal integrity. This ensures that the encoded spikes represent meaningful events, which results in more accurate and reliable time series predictions and improved overall model performance. Compared to other encoding algorithms, TBR's robustness and efficiency make it an excellent choice for the ePAMeT model.

$$H(k) = \frac{1}{N}\sum_{k=1}^{N}(\mu + \sigma.\alpha_{TR}) \tag{4}$$

Where: k is the number of data items of a time series presented so far for encoding; μ and σ are mean and standard deviation of all values from k=1 to N; α_{TR} is a spike threshold constant.

Model Initialization

The generated spikes are mapped to a predefined number of neurons spatially located in the 3D-SNNcube after the connections between the neurons are initialized using the small-world connectivity (SWC) method. This method generates probabilistically connections between neurons based on their distance in the 3D space, the larger the distance- the smaller the connection weight. For time series, where there is no spatial information available for the input variables, a vector quantization principle is employed, in which similar temporal input variables are mapped to closer spiking neurons in the SNNcube [Tu 2017]. The similarity between the input time series is calculated either based on the raw signals, or based on their spike encoded sequences.

Unsupervised Learning Phase

The 3D SNNcube is trained on the encoded spikes using the STDP learning rule [Song 2000], which governs the rate of synaptic weight updates during the unsupervised learning phase. Some hyper-parameters should be defined, such as the neuron's potential leak rate (the rate at which membrane potential decreases over time), the neuron's refractory time (the time a neuron cannot fire after emitting a spike), the STDP learning rate for updating connection weights, the firing threshold (the membrane potential level for a neuron to generate a spike), the number of training iterations, and the long-distance probability.

Supervised Learning Phase

The computationally efficient dynamic evolving Spike Neural Network (deSNN) is trained as an output classifier/regressor using labelled information associated with input samples [Kasabov 2013].

Recall procedure

When a new input spatio-temporal or temporal sample X of K variables, each measured for a time duration T, is entered for a recall to a trained NeuCube model, the sample X is first encoded as K input spike sequences, then propagated through the trained 3D SNNcube and the patterns of spiking activity of the SNNcube over the time of presentation T are send to the trained classifier/regressor for calculating the output for the input sample X.

NeuCube parameter optimization

For better performance during the learning process of a NeuCube model, several parameters need to be optimized using the prediction accuracy as an objective function.

3. The Proposed ePAMeT Framework and Method

A functional diagram of the proposed ePAMeT framework is shown in Fig. 1.

The main hypothesis is: Once an SNN model is trained on a full scale of time series variables for prediction, it can generalize using partial time series variables, both in terms of number of variables used and their time length. The rationale behind the hypothesis is rooted in the principles of brain-inspired SNNs and their ability to encode and generalize temporal patterns. A SNN model can accommodate the time series similarity information as spatial coordinates. During training, the time series data is encoded into spikes using spike-time dependent plasticity (STDP) learning, which guarantees that the connection weights between the neurons capture temporal associations between the input variables. These brain-inspired principles are manifested in SNN architectures, such as NeuCube.

Once a SNN is trained on K time series variables, each measured in a time length of T, the model can be recalled on a smaller number of variables K1<K and time of measurement T1<T, as the already created connections during learning can be indirectly activated even when some input variables are missing in the recall procedure following the principles of polychronization [Izhikevich 2006] and synfire [Ikegaya 2004]. "Polychronisation" is a term that defines groups of neurons activated together under certain inputs through making connections between them. The polychronization principle allows the SNN to recall learned temporal associations even when some of the original input variables are not present, as the remaining variables can indirectly activate these connections. "Synfire chains" is a term describing a sequential firing of groups of neurons in both brains and neural networks, under a single stimulus. It ensures that temporal information is preserved and propagated through groups of neurons rather than through a single one, enabling the model to maintain its predictive capabilities even with partial input data. These connections can be activated even for a shorter time of input variables rather than for the full time used in training the full model. When some groups of neurons are activated, they activate sequentially other neuronal groups as a firing chain, even without having input data presented.

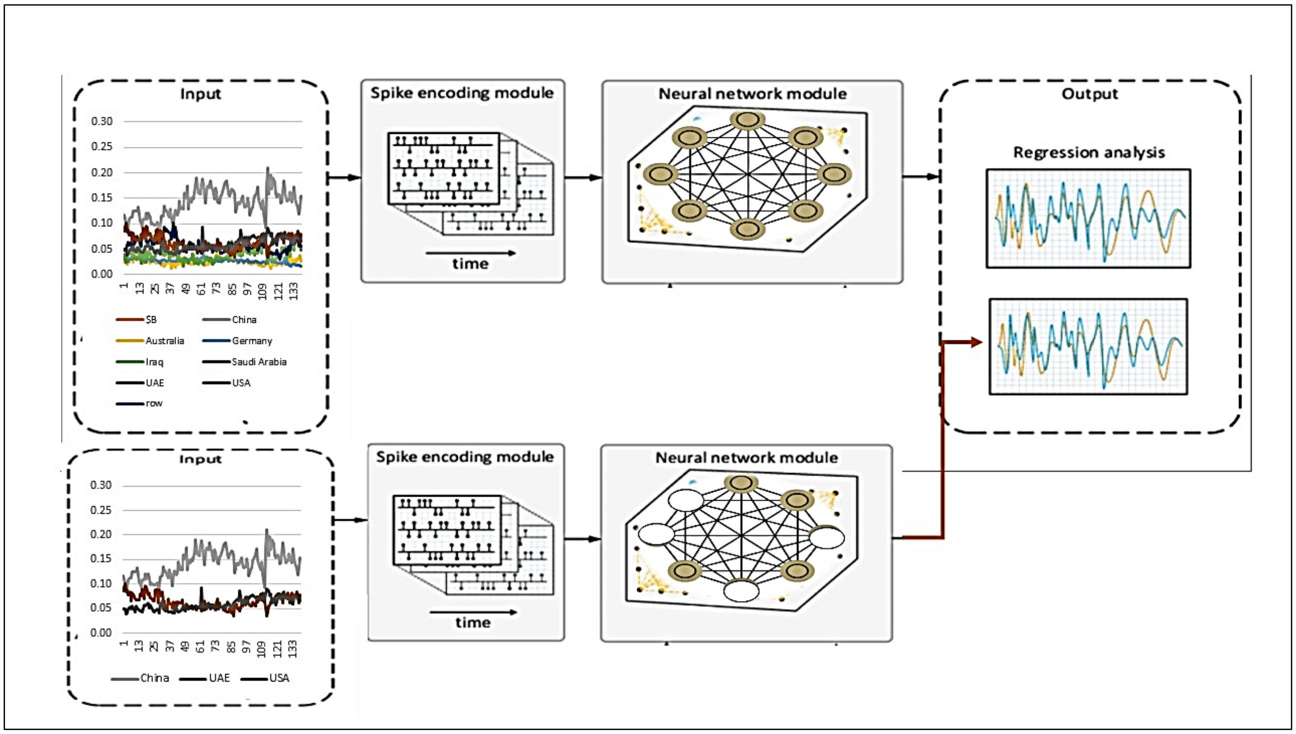


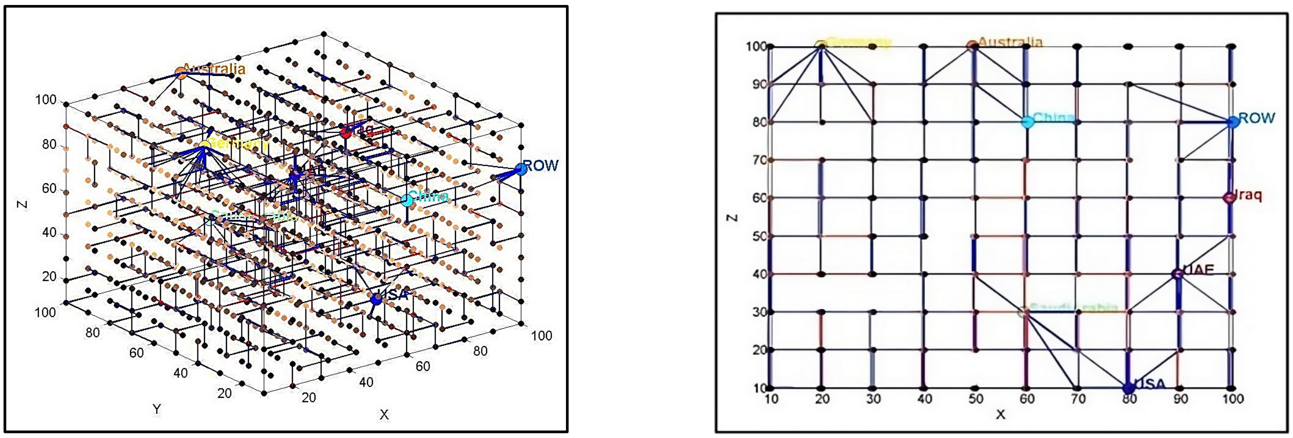
Fig. 1 The proposed ePAMeT framework, consisting of: a spike encoding module; 3D SNNcube; regression module for each of the training (the upper part) and recall (lower part) procedures, exemplified by the used in the next section case study data. Training is applied on all data, while for recall a smaller number of input varianles are used for a shorter time.

The proposed ePAMeT method consists of the following steps:

1. Defining a full set of K time series variables for the prediction of a targeted output time series variable.
2. Encoding the K time series variables into spike sequences.
3. Spatially mapping the K input variables into a 3D SNN using, for example, the graph mapping algorithm [Tu 2017], illustrated in Fig. 2a. This algorithm maps temporal data features into spiking neurons of a 3D SNNcube, so that similar time series (similarity is measure either on original data or after spike encoding) are mapped to closer neurons in the 3D space of the SNNcube. This is a principle first suggested in SOM by Kohonen, but used here not for vector-based, but for temporal-based data [Tu 2017].
4. Training the 3D SNN with the STDP unsupervised learning and analyzing the connectivity. An example is shown in Fig. 2b.
5. Training a deSNN output regressor.
6. *Extracting explainability information as new knowledge.* This is achieved by calculating a variable/feature interaction network (FIN) graph based on the number of spike exchanges (information exchange) between clusters of the input neurons during learning. The input neurons receive positive or negative spikes that are propagated to make other neurons in the SNNcube spike at other times (example is given in Fig.3a,b) resulting in changing the connection weights. The more spikes exchanged between two neurons corresponding to two input variables, the more important they are for the predictive model on both full and partial sets of input variables, as illustrated in Fig. 4 and 5. The process of FIN graph calculation includes the following steps: clustering the spiking neurons in the SNNcube based on the strongest connections from input neurons; counting spikes from a neuronal cluster Ni to cluster Nj at two consecutive time units; this number of spikes is assigned as a weight between graph nodes Ni and Nj. This count represents a temporal association

(correlation) between two spatially distributed in the SNNcube neurons Ni and Nj. A large number may represent not only correlation, but temporal causality as well. This is a way for knowledge discovery from multiple time series.

7. Selecting a subset of K1 variables, measured over time T1 < T, recalling /testing the model and calculating the association and generalization accuracy.
8. Adapting/evolving the SNN model on new data, including new variables for a specific application, if required.



(a) *(b)*

Fig. 2a. Spatial mapping of 8 time series variables from the case study 1 data [HTTP ComTrade] into an SNN of 1,000 neurons with the use of a graph-matching algorithm [Tu 2017] and connectivity between neurons after unsupervised training of the SNN, where connections represent spatio-temporal associations between input variables. Fig. 2b. represents a 2D projection of the connectivity of the trained SNN. Blue lines are positive connections (excitatory synapses), while red lines are learned negative connections (inhibitory synapses).

When a SNN model, once trained on full data, is recalled either on the same set of variables and data or on a different one, different areas of the SNN model are activated at different times of the presentation of the input data in order to activate a certain output neuron that contains the output value. This pattern of SNN activation can be represented as a fuzzy rule, which is a new knowledge that helps understand the data and the behaviour of the ePAMeT model. Thus, the proposed model is not a black box, but facilitating knowledge discovery as evolving spatio-temporal rules from multiple time-series [Kasabov 2019]. The rules are in the form of:

IF (the cluster of neurons Ni representing a time series feature Xi *is* changing first) AND

IF (the cluster of neurons Nj representing a time series feature Xj *is* changing second) AND

THEN (the output value (or class) of the output time series variable Y will be Yk at time Tk,

Where both clusters and time intervals are represented as fuzzy terms. These rules change and evolve with more data entered into the model [Kasabov 2023b].

The spatial mapping of variables into a 3D SNN structure based on similarity would allow for the use of new, related to the same problem, variables and their corresponding time series data to train and recall an ePAMeT model at a later stage. This is illustrated on the 2 case studies below.

4. A case Study of ePAMeT on Trade Imports Time Series Data

This and the second case studies in section 5 illustrate the 3 main features of the proposed ePAMeT framework on real data, namely:

a) associative recall: a trained model is recalled on partial number of variables and partial time series;

b) evolvability: incremental training of an already trained model on new variables and their time series;
c) explainability: extracting information and knowledge about the dynamic interaction between the variables.

4.1. Trade Imports Data

International trade plays a crucial role in a globalized world where accurate predictions of exports and imports have become a fundamental aspect of economic projections. While the volume of imports leads to an estimate of the domestic demand for foreign goods, the value of imports is affected by fluctuations in international prices. In 2020, India emerged as one of the world's fastest-growing economies and has become a major player in the global economy with a high growth rate [HTTP WB-country; HTTP OECD; HTTP ETimes]. In 2020, India's imports accounted for 2.4% of global imports, with the top imports being crude petroleum, electronics, and machinery, imported mostly from China, the United Arab Emirates, and the United States [HTTP Global; HTTP OEC].

The proposed ePAMeT framework is exemplified here on a case study involving predictive modelling of trade data, particularly when limited features are presented on recall. This case study includes 139 observations of monthly imports of goods from eight Indian trading partners over the period January 2011 to July 2022, obtained from the United Nations Comtrade [HTTP ComTrade].

The data consists of India's major imports from partners (input variables), including Australia, Germany, Saudi Arabia, United Arab Emirates, the United States, and other countries as Rest of the World (ROW). The goal is to create a predictive model on the available trading time series data to predict future trading between India and China and then to recall this model in future on a smaller number of input variables, measured at a shorter time. In this model, the share of monthly imports as a proportion of total imports is used instead of the values of imports.

Using a sliding window approach, one data point at a time, 127 overlapping samples have been generated from the original dataset. The sample window is set to a size of 12 to represent 12 consecutive time points (temporal features) and eight countries (spatial features), resulting in 96 data points per sample. The target feature is the import to India from China, India's major trading partner. The model should predict China's share of total India's imports for the following month based on its interconnection with other features and historical values.

4.2. Creating the ePAMeT model

The proposed ePAMeT model encodes time series into spikes using the threshold-based representation (TBR) encoding algorithm (see Eq. 4). One of the advantages of encoding time series into spike sequences using a threshold-based method is that in this way, noise (below the threshold) is eliminated. This makes the algorithm ideal for trade data analysis as it focuses solely on identifying differences between successive temporal characteristics while eliminating chaotic perturbations [HTTP WB-commodity].

The following ePAMeT parameter values are used in the experiment below, as explained in sections 2 and 3: spike threshold 0.5; small world (SW) connectivity radius 2.5; STDP learning rate 0.01; firing threshold of the spiking neurons in the SNN 0.5; refractory time 6 units; membrane potential leak rate of 0.002. Spiking activity in the SNNcube is shown in Fig.3 a,b. The dynamic evolving deSNN regressor is used in a supervised mode. The initial connection weights of the output neurons are set to zero. The connections between connected neurons [i, j] are calculated using the Rank-Order (RO) method of the first incoming spike with the modulation factor mod=0.8. The spike-driven synaptic plasticity (SDSP) learning rule adjusts these connections with a drift value d = 0.005, increasing their weight when spikes arrive and decreasing it if no spikes occur at a time unit (Eq. 3).

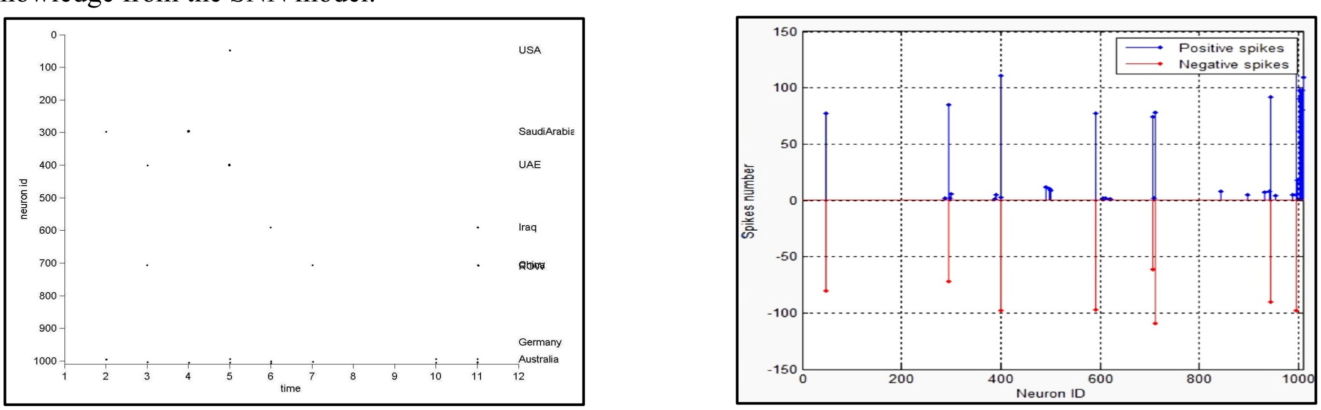
4.3. Experimental Results, Analysis, and Knowledge Discovery

The dataset was split in half so that 50% of the data were used for training, and the other 50% were used for incremental learning and model validation. After the unsupervised learning phase is complete, the connections between the input neurons in the trained SNN are displayed in Figures 2a and 2b. The intensity of each neuron's activity is indicated by color; the brighter the color, the higher the activity. Positive (excitatory) connections between neurons are shown by blue lines, while negative (inhibitory) connections are represented by red lines. The spike raster plot in Figure 3a displays the activity of multiple neurons over time, where each dot corresponds to the occurrence of a spike from a particular neuron. Figure 3b shows the amount of positive and negative spikes being emitted by each neuron during the learning stage.

The learned interactions between the input neurons that represent the trading partners' imports are illustrated by the feature interaction network (FIN) graph (Fig. 4a). The FIN effectively explains the impact of trading patterns between India and its partners, highlighting significant associations such as the strong influence of imports from China on other countries. This visual representation provides a clear understanding of the results, making the analysis accessible and informative.

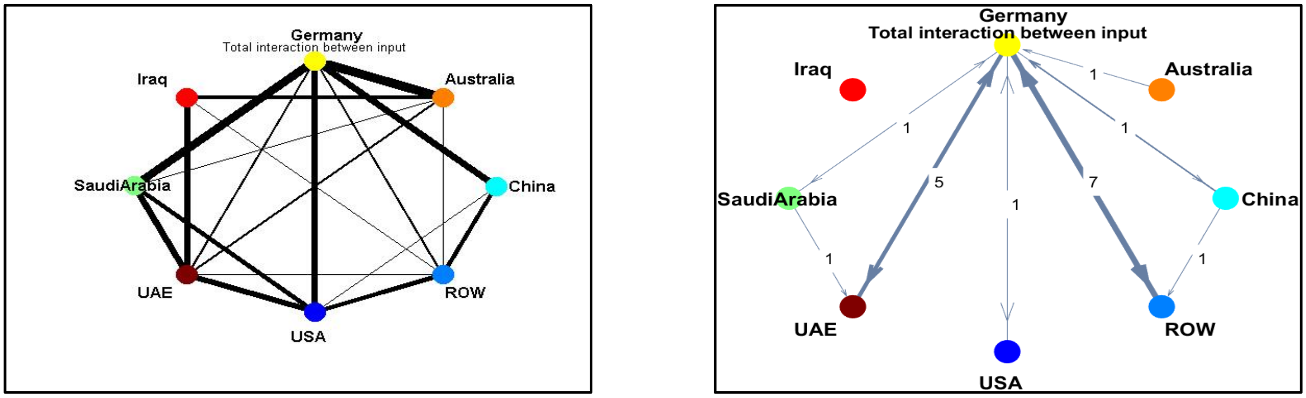
In the FIN, the influence of activity between trading partners is represented by connected straight lines. The denser the connection, the greater the effect between the partners. FIN shows that imports from China have a direct impact on Germany, the USA, and the rest of the world and are indirectly influencing/influenced by imports from Australia, Iraq, Saudi Arabia, and the United Arab Emirates. The thickest bond, as shown in the FIN, indicates that imports from Germany have a strong association with other countries. ePAMeT further enhances understanding through a weighted directed graph (WDG) representation (Fig. 4b), which provides insights into causality by displaying spiking activity between interconnected neurons within the network.

During unsupervised STDP learning in the SNN, spikes are transmitted across synapses between neurons, resulting in changes to the connection weights, forming clusters of connected neurons to each of the input variables (Fig. 5a). The relative size of the clusters is shown in Fig. 5b. This is important information extracted as new knowledge from the SNN model.



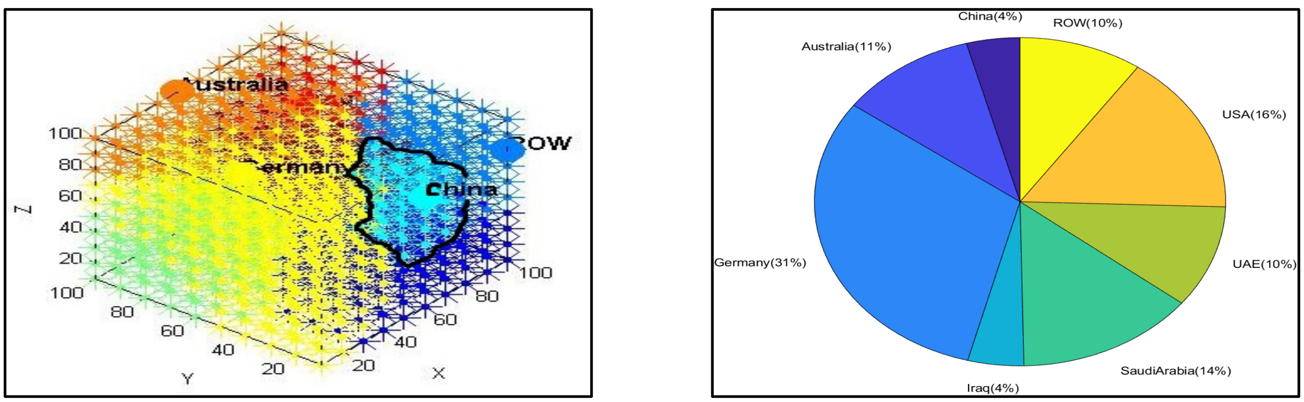
(a) *(b)*

Fig. 3a. A spike raster plot provides a visual representation of the spiking activity across multiple neurons over time, where each dot corresponds to the occurrence of a spike from a particular neuron. The horizontal axis represents time, while the vertical axis represents different neurons. Fig. 3b. shows the positive and negative spike amount emitted by each neuron. Most of the spikes come from the input neurons.



(a) *(b)*

Fig.4. Explainability and knowledge discovery: (a) Total information exchanged between the neuronal clusters of partners variables based on connection weight clustering; the thicker the lines, the more spikes are exchanged between the clusters. (b) Weighted directed graph of total information exchanged between features' connected neurons based on spike communication clustering method.



(a) *(b)*

Fig. 5. Explainability and knowledge discovery: (a) Clusters of spiking neurons connected to each of the input variables as a result of the STDP learning in the SNN; (b) their proportion. A dominating trade partners are Germany, USA and Saudi Arabia.

4.4. Using the ePAMeT model to predict future imports with partial input information

A major feature of ePAMeT is its ability to perform training on a full dataset; while testing and validation can be carried out on a smaller subset of features from the original dataset. The experiments followed an iterative process, recalling the model with reduced sets of input variables (K1 < K) measured during a shorter period (T1 <T). For the time interval T1, it was set to 50% of the total time-frame T (T = 127). Table I demonstrates that the ePAMeT model can be trained and tested on a full input dataset (K=8) with high accuracy, achieving a Root Mean Square Error (RMSE) of 0.02. The RMSE represents the square root of the average squared differences between predicted and observed values. Other common performance measures for predictive models include Mean Absolute Error (MAE), which measures the average magnitude of errors in a set of predictions without considering their direction, and Mean Absolute Percentage Error (MAPE), which measures the size of the error in percentage terms. Both metrics are valuable and often used alongside RMSE to provide a comprehensive evaluation of model performance. However, RMSE is preferred in this study because it penalizes larger errors more than MAE and MAPE, which is crucial for our application where significant deviations can have substantial impacts [Hyndman 2006, Willmott 2005, Chai 2014].

TABLE I
THE PREDICTED PATTERN OF INDIA'S IMPORTS FROM CHINA VALIDATED ON FEWER INPUT FEATURES (FROM 8 TO 7,6,..,1) MEASURED FOR 50% OF THE FULL TIME USED FOR TRAINING

Time Frame for recall [T1/T]	Number of features for recall [K1]	Available Input Features								RMSE
		China	Australia	Germany	Iraq	Saudi Arabia	UAE	USA	ROW	
0.5	8 *(full model)*	1	1	1	1	1	1	1	1	0.02
0.5	7	1	1	1	1	1	1	1	0	0.02
0.5	6	1	1	0	1	1	1	1	0	0.03
0.5	5	1	0	0	1	1	1	1	0	0.03
0.5	4	1	0	1	0	0	1	1	0	0.03
0.5	3	1	0	0	0	0	1	1	0	0.02
0.5	2	1	1	0	0	0	0	0	0	0.04
0.5	1	1	0	0	0	0	0	0	0	0.03

This level of *association accuracy* is maintained even when the model is tested on a smaller portion of the same data, with only slight differences in RMSE when validated on K1=3, 6, and 7 features. This remarkable consistency showcases the model's robust performance, even with fewer input features (Table I). While RMSE has been highlighted as a primary metric due to its sensitivity to larger errors, we recognize that reducing the number of input variables may impact other indicators of prediction quality, such as MAE and MAPE. Further analysis could consider these metrics to provide a more comprehensive evaluation of the model's performance under varying conditions of input reduction. By using RMSE, we ensure that the model's predictions are not only accurate on average but also resilient to larger deviations, which is critical for reliable time series forecasting.

Training a model of 8 trading variables to predict trading inputs from China to India and recalling this model using 8,7 or 3 variables resulted in RMSE accuracy of 0.02 and if it is recalled only on one variable (imports from China) the RMSE is 0.03. This is several times lower than if univariate model was trained and recalled only on one variable (imports from China) (RMSE 0.25) using linear regression techniques. More comparisons with the use of other traditional machine learning methods are presented in section 4.5 and Table II.

The results consistently demonstrate an impressive temporal (less time used) and spatial (a smaller number of input variables) association accuracy. Notably, the model effectively preserves associations as spatio-temporal connections between neurons, retaining its initial connections established during the learning phase when recalling the model on a subset of input variables. In financial time series prediction, the proposed model successfully predicts trading patterns using a subset of trading partners' data. By reducing the number of input features and the length of the observation window, ePAMeT maintained high predictive accuracy. Effectiveness was measured using metrics such as RMSE, which demonstrated that ePAMeT's accuracy remained stable even when the model was tested with fewer input features and shorter time frames, showcasing its robustness and adaptability. These predictive capabilities can help businesses optimize supply chains by predicting market fluctuations, such as changes in import patterns. Policymakers can use these insights to reduce economic risks by diversifying trade relationships and creating more stable trade policies.

4.5. Comparison of the prediction accuracy of ePAMeT against other methods

Further experiments have been conducted utilizing established neural network models. The accuracy of the ePAMeT model was compared against various other methods (Table II). The comparison is based on the Root Mean Squared Error (RMSE), which measures the deviation of the predicted values from the actual ones. The ePAMeT method achieved an RMSE of 0.02, outperforming traditional methods like K-Nearest Neighbor (KNN) and Multi-Layer Perceptron (MLP), which showed higher RMSE values due to their requirement for complete datasets and inability to handle partial data effectively. These traditional methods lack the adaptability and incremental learning capabilities of ePAMeT, which allow it to evolve with new data while maintaining accuracy. Methods like DENFIS and EFuNN performed closer to ePAMeT but are less effective in handling evolving data streams and partial input. It's worth noting that the comparison presented in Table II was performed using all input variables. However, the most important feature of the proposed ePAMeT is that it can predict outcomes, even when some input variables are not available, without sacrificing accuracy (see Table I). This feature sets ePAMeT apart from other methods listed in the table, which, once trained on a set of variables, cannot be recalled on a subset of these variables.

TABLE II

COMPARISON OF PREDICTION MODEL PERFORMANCE

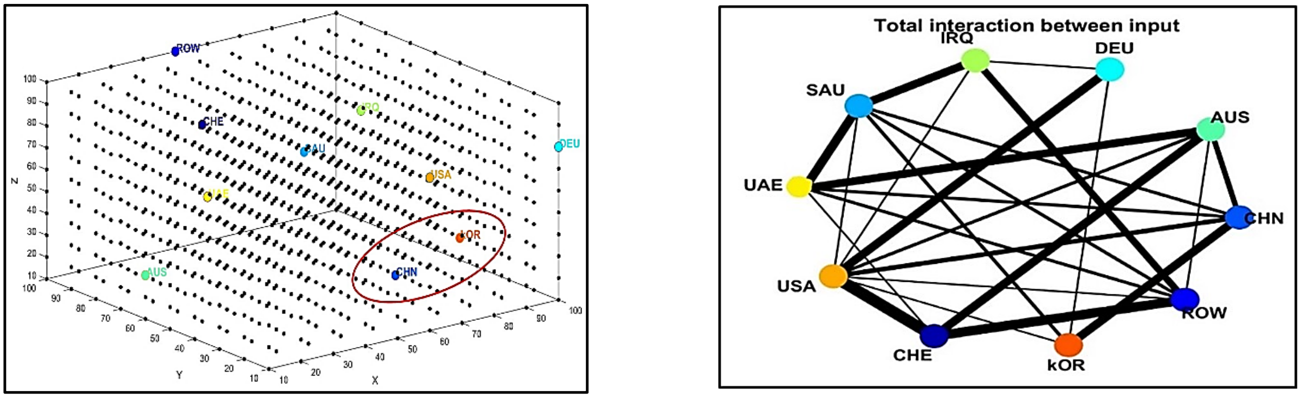
Model	RMSE
K Nearest Neighbor (KNN) [HTTP NeuCom]	0.194
Multi-Layer Perceptron (MLP) [HTTP NeuCom]	0.182
Radial Basic Function [HTTP NeuCom]	0.189
Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS) [HTTP NeuCom, Kasabov 2002]	0.0224
Evolving Fuzzy Neural Networks (EFuNN) [HTTP NeuCom, Kasabov 2001]	0.0266
Predictive Associative Memory for Time Series (ePAMeT-SNN)	**0.0200**

4.6. Evolvability of the ePAMeT model on new variables and their relevant time series data

The ePAMeT model is capable to integrate and learn new variables without requiring pre-training on the previous ones. The ePAMeT model, initially trained on time series data from eight of India's import partners, is enhancing its predictive scope by incorporating data from two additional partners, Switzerland (CHE) and the Republic of Korea (KOR), without the need for pre-training on the existing dataset (Fig. 6a). The results are evaluated in terms of how much the trade between India and these two additional partners would impact the prediction of the trade between India and China.

The explainability of ePAMeT is improved after the introduction of the two new partners. This results in an increase of the exchange of information, particularly with KOR, due to its geographical proximity to the existing data clusters. Figure 6a shows the mapping of the new variables KOR and CHE into a NeuCube model, along with the old 8 variables. Fig.6b shows the dynamics of information exchange between the now 10 input features after further training the model on two new features. When compared with Fig.4a, here we see a strong association between imports from KOR and CHN to India.

After introducing 2 new variables into the model and further training the model on the two corresponding time series, the model was tested again on predicting the output variable, with a RMSE slightly lower by 4%. In this case the introduction of new variables reduced slightly the predictive error, but more importantly it reveals better trading dynamics between the trading partners as shown in Fig. 6b.



(a) *(b)*

Fig.6 (a) Incremental adding of 2 new features (COR and CHE) to the already mapped 8 features in SNN AM using the graph mapping algorithm, with similar time series mapped into nearby neurons in the 3D space, showing proximity between mapped CHN and KOR. (b) Feature Interaction Network between all 10 features over time, including both the old 8 features and the new 2 ones (KOR and CHE).

5. ePAMeT Model on a Case Study of Commodity Data

5.1. Case Study on Time Series Commodity Price Data

A second case study on commodity market prices was conducted to demonstrate the general scope of the proposed model. Here, an ePAMeT model is developed to analyze and predict commodity market prices with the same objectives as listed for case study 1 in the previous section.

Commodity prices are influenced by the ongoing slowdown in the global economy, driven by a surge in price pressures that outpaces the decline in global inflation rates. This complex interaction of economic forces contributes to the dynamic nature of commodity markets. According to a recent assessment by the World Bank [HTTP WB-commodity], the energy sector encountered a notable increase, with energy prices escalating by 6% in July 2023. Furthermore, the report indicates that food and metal prices increased by 0.9% and 0.4%, respectively, during the same month. Precious metals also increased by 0.8%. Notably, this was driven by a 3.8% surge in silver prices. In contrast, gold witnessed a modest 0.4% increase, while platinum experienced a 2.2% decline.

For this case study, market prices of eight commodities have been downloaded from the International Monetary Fund (IMF) Commodity Portal [HTTP IMF]. The selected commodities represent eight input features (Table III). And the predicted feature is the market price of a *platinum* precious commodity in the next month.

The ePAMeT model is exemplified by a case study involving predictive modelling in a commodity dataset from January 2010 to May 2023. The dataset contained 161 observations of the monthly market prices of the eight selected commodities.

Utilizing a sliding window approach with a step size of 1, a total of 149 overlapping samples have been generated from the original dataset. This method involves moving the window by a single data point at a time to generate a series of data subsets, each constitutes a sample for analysis. The chosen sample window size is set to 12 months as consecutive temporal data points, resulting in 14,304 spatio-temporal data points organized sequentially and synchronized with time. This structured dataset is then used to continuously provide input to the model over time. Our analysis focuses on the platinum commodity in an effort to understand and predict the price dynamics and commodity market behavior associated with it.

The generated samples were split in half: 50% were used for training, and the remaining half for incremental learning and validating the model. The same parameter values are used in the NeuCube mode as in Section 4.

TABLE III

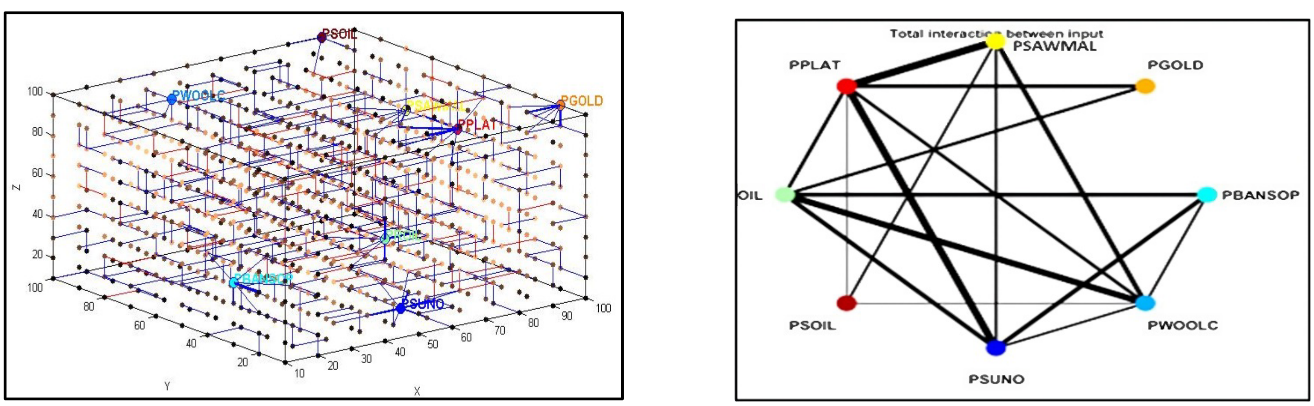
THE SELECTED COMMODITIES AS INPUT FEATURES

No.	Spatial feature	Description
1	PBANSOP	Bananas, US$ per kiloton
2	PGOLD	Gold, US$ per thousand troy ounces
3	PSAWMAL	Sawn wood, US$ per thousand cubic meters
4	PPLAT	Platinum, US$ per thousand troy ounces
5	PROIL	Rapeseed oil, US$ per kiloton
6	PSOIL	Soybean Oil, US$ per kiloton
7	PSUNO	Sunflower oil, US$ per kiloton
8	PWOOLC	Wool coarse, US cents per kiloton

5.2. Modelling, Experimental Results, Analysis, and Knowledge Discovery

After the spatial mapping of temporal variables according to the similarity of the time series as spatial coordinates [Tu 2017], the spike-time dependent plasticity (STDP) learning [Song 2000] is performed on the encoded spikes. Consequently, the connection weights between neurons reflect the temporal relationships between the input commodities. Figure 7a shows the connectivity in the reservoir during global unsupervised learning on market price data of 8 commodities. The similarity between Platinum and Gold, as precious metals, are properly mapped next to each other in the SNNcube.

The feature interaction network (FIN) graph in Fig. 7b shows the learned information exchange between the input neurons that represent the commodity market prices. According to the FIN graph, the analyzed feature, 'Platinum,' has the maximum level of interaction with other features. There is a strong direct influence with PGOLD, PSUNO, and PSAWMAL and a moderate relationship with PWOOLC, PROIL, and PSOIL. The other precious metal, PGOLD, is strongly interacted with PPLAT and PROIL.

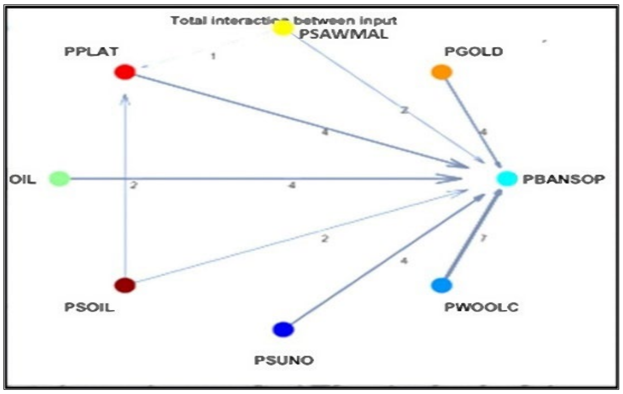


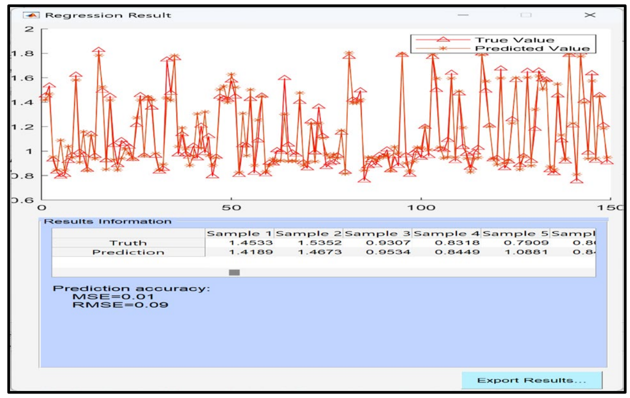
(a) *(b)*

Fig. 7a. The connectivity in the reservoir during global unsupervised learning on market price data of 8 commodities. (b) Total information exchanged between the neuronal clusters of commodities, weighted by the thickness of the connections.

Using the spike communication clustering method, the Weighted Directed Graph (WDG) displays the direction and magnitude of influence between input features (Fig. 8a). The graph demonstrates that PPLAT influences PBANSOP directly and is influenced by PSOIL. The ePAMeT model achieves an RMSE accuracy of 0.09 through 4-fold cross-validation (Fig. 8b), ensuring robust and generalizable performance. The process involves dividing the dataset into four equal-sized folds; three folds are used for training while one is for testing in each iteration. The model is trained with optimized parameters and evaluated on the testing set, with RMSE calculated for each fold to measure the deviation of predicted values from actual ones. The final performance is reported as the average

RMSE across all folds.





(a) (b)

Fig. 8a. Measured directed graph of total information exchanged between the 8 features' connected neurons based on spike communication clustering method; (b) Regression results with a prediction accuracy of RMSE=0.09 after 4-fold cross-validation.

5.3. Using the ePAMeT to predict future price with a smaller number of input commodity time series variables measured at a shorter time

The efficiency of the ePAMeT model in capturing and forecasting complex dynamics in the commodities market is validated by its application for analyzing and predicting commodity market prices. In accordance with the methodology outlined in section III, the ePAMeT model was originally employed for the whole input stream (K=8) at a full-time window T. Subsequently, the experiments involved a repeating procedure whereby the model was recalled by using reduced datasets of input variables. The recall procedure is iterated for subsets of data that are smaller in size (K1<K) and measured during mush shorter interval (T1 <T) until a desirable degree of precision is achieved. The time period T1 is set to 50% of the whole timeframe of T = 149. Table IV demonstrates that K1=4 and T1=75 is a good option for predicting the market price of platinum when the set of PBANSOP, PSAWMAL, PSOIL, and PPLAT historical values are used measured at the first 75 time points, as in this case, the model has the same level of accuracy as when using the full input dataset of 8 variables measured at 149 time points (Table IV).

5.4. Evolvability of the ePAMet model on new variables

In this section, we extend the capabilities of the ePAMeT model, to include time series data for two additional commodities: Fine Australian Wool (PWOOLF) and Palladium (PPALLA). This inclusion is performed without the necessity for retraining on the previously used datasets, demonstrating the model's adaptability and robustness. The inclusion of PWOOLF and PPALLA aims to evaluate their influence on future price predictions for platinum, offering insights into commodity market interdependencies.

TABLE IV

THE PREDICTED MARKET PRICE OF PLATINUM COMMODITY WITH REDUCED INPUT VARIABLES (FROM 8 TO 7,6,…, 1) AND REDUCED RECALL TIME OF 50% OF THE TRAINING TIME

Time Frame for recall [T1/T]	Number of features for recall [K1]	Available Input Features								RMSE
		PBANSOP	PGOLD	PSAWMAL	PPLAT	PROIL	PSOIL	PSUNO	PWOOLC	
0.5	**8 (full)**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0.09**
0.5	7	1	1	1	1	1	1	0	1	0.11

0.5	6	1	0	1	1	1	1	0	1	0.19
0.5	**5**	**1**	**0**	**1**	**1**	**0**	**1**	**0**	**1**	**0.09**
0.5	**4**	**1**	**0**	**1**	**1**	**0**	**1**	**0**	**0**	**0.09**
0.5	3	0	0	1	1	0	1	0	0	0.24
0.5	2	0	0	0	1	1	0	0	0	0.25
0.5	1	0	0	0	1	0	0	0	0	0.28

The inclusion of these commodities benefits the model's explainability. Initially, PWOOLF and PPALLA did not participate in the model's spiking activity. However, post-integration, there is a notable increase in the exchange of information, which illustrates the dynamics before and after the inclusion of these commodities (Fig. 9 vs Fig.7b).

When the adapted model of now 10 features, including the 2 new ones, was tested on the same data to predict PPLAT next month, there was no change in the RMSE prediction error. This may suggest a limited significance of PWOOLF and PPALLA within the current model framework.

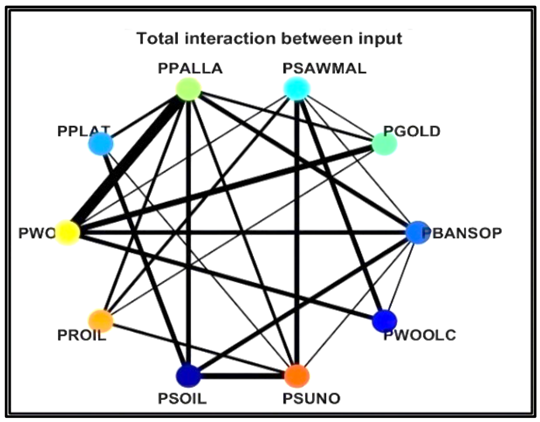


Fig.9. Enhanced total information exchange between the neuronal clusters of all ten partner variables post-training, highlighting the increased engagement from the two newly introduced features when compared with Fig.7b.

6. Discussions and Conclusion

The proposed in this paper ePAMeT model has demonstrated its capability as a useful tool in predictive analysis for time series. Its adaptability to different features over time and space without a loss in accuracy makes it a promising tool for modelling and understanding of dynamic and uncertain environments.

ePAMeT overcomes a significant problem of traditional machine learning models that often require complete datasets with all temporal variables for both training and recall, limiting their applicability, especially in scenarios where data may be incomplete or only a subset of variables is available [Kasabov 2002; Li 2017; Sánchez 2016; Singh & Saraswat 2017; Chin 2016; Kasabov 2001; Yang 2022; Pedrycz 2018].

Our model's capacity to maintain associations and make accurate predictions even with a reduced set of input variables is of immense practical significance. In various real-world applications, such as financial forecasting, environmental monitoring, and crisis response, data may be scarce, incomplete, or expensive to collect comprehensively. The proposed ePAMeT unique behavior enables it to extract valuable insights and provide accurate predictions, even when operating with a smaller subset of variables at a time, without compromising accuracy.

Furthermore, the proposed ePAMeT method can be used to extract temporal fuzzy rules to be used for comparison analysis between fully trained and partially recalled ePAMeT, adding to the explainability of the model [Kasabov 2023b; Song & Kasabov 2005]. A major advantage of ePAMeT is that it can be incrementally evolved on new data and new variables as demonstrated in the paper.

The proposed ePAMeT is based on SNN and due to the spike encoding of raw time series data, the model is more robust to noise, as noise does not cause spike generation, depending on the threshold (Sengupta 2017). In terms of missing features, once an ePAMeT model is created on full set of variables and data, it can be recalled on partial set of variables. Missing values within a time series can be interpolated if appropriate. All these options, while valid in principle, need to be further studied in details, e.g. how much noise and missing values, which is currently an objective of a next study.

ePAMeT model offers a solution to the challenges of predictive time series modeling in dynamic and uncertain environments. By allowing for flexible recall using partial data, supporting ongoing evolution with new variables, and enhancing explainability through dynamic interaction networks, ePAMeT overcomes the significant limitations of existing models. These features make ePAMeT a robust tool for various applications.

Further use of ePAMeT can be anticipated in several problem areas, such as:

- building evolving models for brain-to-computer and brain-to-brain communication [Kelsen 2020];
- building an evolvable system for control of human prosthetics [Kumarasinghe 2019];
- predicting health problems using environmental time series [Kasabov 2016];
- predicting earthquakes [Kasabov 2016];
- pollution prediction based on multisensory streaming data [Kasabov 2016; Liu 2021];
- predicting petroleum imports [Abouhassan 2022];
- financial time series prediction using online news and other variables [Abouhassan 2023].
- ePAMeT can be further developed for large-scale evolving integrated multi-model systems for online multiple time series prediction [Pears 2012].

References

(Abouhassan 2022): Abouhassan I, Kasabov N, Popov G, Trifonov R (2022) “Why Use Evolving Neuro-Fuzzy and Spiking Neural Networks for incremental and explainable learning of time series? A case study on predictive modelling of trade imports and outlier detection,” IEEE 11th International Conference on Intelligent Systems (IS), Warsaw, Poland, 2022, pp. 1-7, https://doi.org/10.1109/IS57118.2022.10019673.

(Abouhassan 2023): AbouHassan I, Kasabov N, Jagtap V, Kulkarni P (2023) “Spiking neural networks for predictive and explainable modelling of multimodal streaming data with a case study on financial time series and online news,” Sci Rep 13, 18367. https://doi.org/10.1038/s41598-023-42605-0.

(Agnes 2012): Agnes E, Erichsen R, Brunnet L (2012) “Model architecture for associative memory in a neural network of spiking neurons,” Physica A: Statistical Mechanics and its Applications, Vol.391, Issue 3, pp 843-848, ISSN 0378-4371, https://doi.org/10.1016/j.physa.2011.08.036.

(Ang 2011): Ang CH, Jin C, Leong PH W, Van Schaik A (2011) “Spiking neural network-based auto-associative memory using FPGA interconnect delays,” International Conference on Field-Programmable Technology, New Delhi, India, pp. 1-4, https://doi.org/10.1109/FPT. 2011.6132701.

(Benuskova 2007) Benuskova, L., N. Kasabov (2007) “Computational neuro-genetic modelling, Springer, NY.

(Chai 2014): Chai T, Draxler RR (2014), "Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature," Geosci. Model Dev., 7, 1247–1250, https://doi.org/10.5194/gmd-7-1247-2014, 2014.

(Chin 2016): Chin WH, Loo CK, Seera M, Kubota N, Toda Y (2016) “Multi-channel Bayesian Adaptive Resonance Associate Memory for on-line topological map building,” Applied Soft Computing, Volume 38, Pages 269-280, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2015.09.031.

(ElSaid 2019): ElSaid A, Benson S, Patwardhan S, Stadem D, Desell T (2019) “Evolving Recurrent Neural Networks for Time Series Data Prediction of Coal Plant Parameters,” In: Kaufmann, P., Castillo, P. (eds) Applications of Evolutionary Computation.

EvoApplications 2019. Lecture Notes in Computer Science(), vol 11454. Springer, Cham. https://doi.org/10.1007/978-3-030-16692-2_33.

(Gerstner & Hemmen 1992): Gerstner W, Van Hemmen JL (1992) “Associative memory in a network of 'spiking' neurons,” Network 3 139, https://doi.org/10.1088/ 0954-898X/3/2/004.

(Hopfield 1982): Hopfield J (1982) “Neural networks and physical systems with emergent collective computational abilities,” Proc. Nat. Ac.Sc., USA, 79, 2554-2558.

(HTTP ComTrade): https://comtradeplus.un.org/TradeFlow.

(HTTP ETimes): https://economictimes.indiatimes.com/news/economy/indicators/very-strong-economy-imf-division-chief-daniel-leigh-on-indias-growth-trajectory/articleshow/99420331.cms/.

(HTTP Global): https://www.theglobaleconomy.com/India/share_world_ imports/.

(HTTP IMF): Https://www.imf.org/en/Research/commodity-prices.

(HTTP NeuCom): https://theneucom.com.

(HTTP NeuCube): http//www.kedri.aut.ac.nz/neucube.

(HTTP OEC): https://www.oec.world/.

(HTTP OECD): https://www.oecd.org/economy/india-economic-snapshot/.

(HTTP WB-commodity): World Bank Commodities Price Data (The Pink Sheet); https://www. worldbank.org/en/research/commodity-markets, August 2023.

(HTTP WB-country): https://www.worldbank.org/en/country/india.

(Hu 2015): Hu J, Tang H, Tan KC, Gee SB (2015) “A Spiking Neural Network Model for Associative Memory Using Temporal Codes,” In: Proceedings of the 18th Asia Pacific Symposium on Intelligent and Evolutionary Systems, Vol.1, Springer, Cham, https://doi.org/10.1007/978-3-319-13359-1_43.

(Hyndman 2006): Hyndman RJ, Koehler AB (2006), "Another look at measures of forecast accuracy," International Journal of Forecasting, Sciencedirect, Volume 22, Issue 4, Pages 679-688, ISSN 0169-2070, https://doi.org/10.1016/j.ijforecast.2006.03.001.

(Ibad 2022): Ibad T, Abdulkadir SJ, Aziz N et al. (2022, “Hyperparameter Optimization of Evolving Spiking Neural Network for Time-Series Classification,” New Gener. Comput. 40, 377–397 (2022). https://doi.org/10.1007/s00354-022-00165-3

(Ikegaya 2004): Ikegaya Y, Aaron G, Cossart R, Aronov I, Lampl D, Ferster D, et al. (2004) “Synfire chains and cortical songs: temporal modules of cortical activity,” Science 304, 559–564.

(Indiveri 2015): Indiveri G, Corradi F, Qiao N (2015) “Neuromorphic architectures for spiking deep neural networks,” IEEE Int. Electron Devices Meeting (IEDM).

(Izhikevich 2006): Izhikevich EM (2006) “Polychronization: computation with spikes,” Neural Comput. 18(2), 245–282.

(Kasabov 2001): Kasabov N (2001) “Evolving Fuzzy Neural Networks for Supervised/Unsupervised On-Line, Knowledge-Based Learning,” IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics, Vol. 31, No. 6, 902-918.

(Kasabov 2002): Kasabov N, Song Q (2002) “DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and its Application for Time Series Prediction,” IEEE Transactions on Fuzzy Systems, Vol. 10, 2, 144-154.

(Kasabov 2012): Kasabov N (2012) “NeuCube EvoSpike Architecture for Spatio-temporal Modelling and Pattern Recognition of Brain Signals,” In: Mana, N., Schwenker, F., Trentin, E. (eds) Artificial Neural Networks in Pattern Recognition. ANNPR 2012. Lecture Notes in Computer Science, vol 7477. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-33212-8_21.

(Kasabov 2014): Kasabov NK (2014) “NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data,” Neural Networks, Vol.52, pp. 62-76, https://doi.org/10.1016/j.neunet. 2014.01.006.

(Kasabov 2016): Kasabov N, et al. (2016) “Evolving spatio-temporal data machines based on the NeuCube neuromorphic framework: Design methodology and selected applications,” Neural Networks 78: 1-14.

(Kasabov 2019): Kasabov N (2019) “Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence,” Springer Nature, p 750, https://www.springer.com/gp/book/ 9783662577134.

(Kasabov 2023a): Kasabov NK (2023) “Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives,” TechRxiv. Preprint. https://doi.org/10.36227/ techrxiv. 23723208.v1.

(Kasabov 2023b): Kasabov N, Tan Y, Doborjeh M, Tu E, Yang J (2023) “Transfer Learning of Fuzzy Spatio-Temporal Rules in the NeuCube Brain-Inspired Spiking Neural Network: A Case Study on EEG Spatio-temporal Data,” IEEE Transactions on Fuzzy Systems, 1-11, 1941-0034, https://doi.org/10.1109/TFUZZ.2023.3292802.

(Kelsen 2020): Kelsen BA, Sumich A, Kasabov N, Liang SHY, Wang GY (2022) "What has social neuroscience learned from hyperscanning studies of spoken communication? A systematic review." Neurosci Biobehav Rev. 2022 Jan;132:1249-1262. doi: 10.1016/j.neubiorev.2020.09.008. Epub 2020 Oct 3. PMID: 33022298.

(Kohonen 1989): Kohonen T (1989) "Self-Organization and Associative Memory" (third edition) Springer-Verlag.

(Kosko 1988): Kosko B (1988) "Bidirectional Associative Memories." IEEE Trans. Syst. Man Cybern. 1988, 18, 49–60. https://doi.org/10.1109/21.87054.

(Kumarasinghe 2021): Kumarasinghe K, Kasabov N, Taylor D (2021) "Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements." Sci Rep 11, 2486 (2021). https://doi.org/10.1038/s41598-021-81805-4; https://www.nature.com/articles/s41598-021-81805-4.

(Lee 2021): Lee JY et al. (2021) "Dopamine facilitates associative memory encoding in the entorhinal cortex," Nature, https://doi.org/10.1038/ s41586-021-03948-8.

(Li 2017): Li L, Pedrycz W, Li Z (2017) "Development of associative memories with transformed data, Applied Soft Computing," Volume 61, 2017, Pages 1141-1152, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2017.05.035.

(Liu 2021): Liu H, Lu G, Wang Y, Kasabov N (2021) "Evolving spiking neural network model for PM2. 5 hourly concentration prediction based on seasonal differences: A case study on data from Beijing and Shanghai."

(López 2014): López-Yáñez I, Sheremetov L, Yáñez-Márquez C (2014) "A novel associative model for time series data mining," Elsevier Science Inc, Pattern Recognition Letters, Volume 41, Issue C, Pages 23 – 33, ISSN 0167-8655,

(Maciąg 2019): Maciąg PS, Kasabov N, Kryszkiewicz M, Bembenik R (2019) "Air pollution prediction with clustering-based ensemble of evolving spiking neural networks and a case study for London area," Environmental Modelling & Software, 118, 262-280.

(Maciąg 2021): Maciąg S, Kryszkiewicz M, Bembenik R, Lobo J, Del Ser J (2021) "Unsupervised Anomaly Detection in Stream Data with Online Evolving Spiking Neural Networks," Neural Networks, Volume 139, Pages 118-139, ISSN 0893-6080, https://doi.org/10.1016/j.neunet.2021.02.017.

(Nuntalid 2011): Nuntalid N, Dhoble K, Kasabov N (2011) "EEG Classification with BSA Spike Encoding Algorithm and Evolving Probabilistic Spiking Neural Network," In 18th International Conference on Neural Information Processing. Shanghai, China, Springer, Heidelberg. LNCS 7062, 451-460.

(Pears 2012): Pears R, Widiputra H, Kasabov N (2012) "Evolving integrated multi-model framework for on-line multiple time series prediction," Evolving Systems, Springer-Verlag Berlin Heidelberg, https://doi.org/10.1007/s12530-012-9069.

(Pedrycz 2018): Pedrycz A (2018) "Bidirectional and multidirectional associative memories as models in linkage analysis in data analytics: Conceptual and algorithmic developments," Knowledge-Based Systems, Vol 142, Pages 160-169, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2017.11.034.

(Petro 2020): Petro B, Kasabov N, Kiss RM (2020) "Selection and Optimization of Temporal Spike Encoding Methods for Spiking Neural Networks," IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 2, pp. 358-370, https://doi.org/10.1109/TNNLS.2019.2906158.

(Sánchez 2016): Cleofas-Sánchez L, García V, Marqués AI, Sánchez JS (2016) "Financial distress prediction using the hybrid associative memory with translation," Applied Soft Computing, Volume 44, 2016, Pages 144-152, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2016.04.005.

(Sengupta 2017): Sengupta N, Kasabov N (2017), "Spike-time encoding as a data compression technique for pattern recognition of temporal data," Information Sciences, Volumes 406–407, Pages 133-145, ISSN 0020-0255, https://doi.org/10.1016/j.ins.2017. 04.017.

(Singh & Saraswat 2017): Singh MP, Saraswat VK (2017) "Multilayer feed forward neural networks for non-linear continuous bidirectional associative memory," Applied Soft Computing, Volume 61, Pages 700-713, ISSN 1568-4946, https://doi.org/ 10.1016/j.asoc.2017.08.026.

(Song & Kasabov 2005): Song Q, Kasabov N (2005) "NFI: A Neuro-Fuzzy Inference Method for Transductive Reasoning," IEEE Transactions on Fuzzy Systems, Volume 13, Issue 6, pp 799-808.

(Song 2000): Song S, Miller K, Abbott L, et al. (2000) "Competitive Hebbian learning through spike-timing-dependent synaptic plasticity," Nat. Neurosci. 3, 919–926.

(Tan 2020): Tan C, Šarlija M, Kasabov N (2020) "Spiking Neural Networks: Background, Recent Development and the NeuCube Architecture," Neural Processing Letters 52:1675–1701, Springer, Science and Business Media, LLC, https://doi.org/ 10.1007/s11063-020-10322-8.

(Thorpe 1998): Thorpe S, Gautrais J (1998) "Rank order coding," In: Computational neuroscience, Springer, pp 113–118.

(Tu 2017): Tu E, Kasabov N, Yang J (2017) "Mapping Temporal Variables Into the NeuCube for Improved Pattern Recognition, Predictive Modeling, and Understanding of Stream Data," in IEEE Transactions on Neural Networks and Learning Systems, vol. 28, no. 6, pp. 1305-1317, https://doi.org/10.1109/TNNLS.2016.2536742.

(Willmott 2005): Willmott CJ, Matsuura K (2005) "Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance," Climate Research, 30(1), 79–82. http://www.jstor.org/stable/24869236.

(Yang 2022): Yang J, Chen G, Wen S (2022) “Finite-time dissipative control for bidirectional associative memory neural networks with state-dependent switching and time-varying delays,” Knowledge-Based Systems, Vol 252, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.109338.

(Yusuf 2017): Yusuf ZM, Hamed HNA, Yusuf LM, Isa MA (2017), "Evolving spiking neural network (ESNN) and harmony search algorithm (HSA) for parameter optimization," 6th International Conference on Electrical Engineering and Informatics (ICEEI), Langkawi, Malaysia, 2017, pp. 1-6, https://doi.org/10.1109/ICEEI.2017.8312365.