PAMeT-SNN: Predictive Associative Memory for Multiple Time Series based on Spiking Neural Networks with Case Studies in Economics and Finance

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Abstract

This paper offers for the first time a novel method for creating Predictive Associative Memories of Time series (PAMeT), where a full set of time series variables is used to create a machine learning predictive model (global learning), and afterward, only a few temporal variables are used at a shorter time to recall the model on new data (local recall). Inspired by human brain processes, PAMeT-SNN leverages the brain-inspired SNN NeuCube and the concept of spatio-temporal associative memories (STAM). PAMeT-SNN is a 4-dimensional spatio-temporal structure. First, it encodes time series data into spike sequences that reflects on the changes in the data over time and then maps the temporal variables into the SNN using temporal similarity to define the spatial locations of the variables in the SNN. It then learns temporal associations between a full set of time series variables, thereby memorizing these temporal associations as spatio-temporal connections between neurons. These connections are activated when only part of the time series data is used to recall the model on new data. The proposed groundbreaking method is exemplified with PAMeT-SNN for predictive modeling on two distinct case study time series data sets: trade dynamics and commodity prices. In these case studies, the method effectively captures the intricate data dynamics, enabling accurate forecasting of future values using a minimal set of variables. The method has the potential to be applied in diverse domains.

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***Abstract*—This paper offers for the first time a novel method for creating Predictive Associative Memories of Time series (PAMeT), where a full set of time series variables is used to create a machine learning predictive model (global learning), and afterward, only a few temporal variables are used at a shorter time to recall the model on new data (local recall). Inspired by human brain processes, PAMeT-SNN leverages the brain-inspired SNN NeuCube and the concept of spatio-temporal associative memories (STAM). PAMeT-SNN is a 4-dimensional spatio-temporal structure. First, it encodes time series data into spike sequences that reflects on the changes in the data over time and then maps the temporal variables into the SNN using temporal similarity to define the spatial locations of the variables in the SNN. It then learns temporal associations between a full set of time series variables, thereby memorizing these temporal associations as spatio-temporal connections between neurons. These connections are activated when only part of the time series data is used to recall the model on new data. The proposed groundbreaking method is exemplified with PAMeT-SNN for predictive modeling on two distinct case study time series data sets: trade dynamics and commodity prices. In these case studies, the method effectively captures the intricate data dynamics, enabling accurate forecasting of future values using a minimal set of variables. The method has the potential to be applied in diverse domains.**

***Impact Statement* —As time series data are widely used in economics, finance, health, engineering, and environment, the proposed method offers a new trend in AI, where a PAMeT-SNN model is created globally on a large number of variables/data and recalled and updated locally on smaller subsets of variables/data.**

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***Index Terms*— Multiple time series, Predictive associative memory for multiple time series, Associative Memory, Spiking neural networks, NeuCube, Imports, Commodity, Economic and Financial time series, Forecasting, STAM, PAMeT-SNN.**

I. Introduction

In today's globalized world, predictive modeling of time series data, such as economic, environmental, etc. is crucial for world prosperity. Many of the time series data are of multiple variables that interact with each other over time. The challenge is how to use a large scale of available 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, still achieving good predictive accuracy.

The paper proposes for the first time a predictive associative memory for time series based on spiking neural networks (PAMeT-SNN). The model utilizes the concept of spatio-temporal associative memory [7]. The proposed PAMeT-SNN addresses some of the limitations of conventional neural network methods to handle non-linear and volatile time series data, and offers a novel comprehensive approach to predict time series with reduced input features without compromising prediction accuracy and explainability, thus contributing to the advancement of explainable AI and incremental learning systems. The case studies in economic forecasting also constitute an unique contribution.

Associative memory (AM) is defined as the ability to learn and remember relationships between items and to recall these associations using partial information. Several AM for time series have been developed using statistical methods [35-38].

Although associative memory is a fundamental concept in brain information processing, the mechanisms underpinning it are still unknown [10]. The human brain learns incrementally from a lot of information and performs spatio-temporal associations between unrelated patterns to robustly store this knowledge in space and time [39,40,41].

This structured knowledge between events and their spatio-temporal attributes is retrieved to make future decisions, when only part of the information is available, either due to limited sources, limited time to make the decision, or both.

Resembling the human brain is one of the most important goals in computational intelligence. AM models based on neural networks have been already proposed in the literature. The Hopfield network [2] and the bi-directional AM [42] are recurrent neural networks that can be used for pattern recognition. However, they deal with vector-based data and not with spatio-temporal or temporal data.

A Hetero-Associative Memory Network (HAM) to model AM using spiking neural networks proved its effectiveness in learning and recalling associations between input and output patterns using simulations [3]. An auto-associative memory based on a spiking neural network (SNN) uses FPGA architectures' vast connection resources to mimic biological brain networks' axons [4]. SNN-based models to encode different memories using different subsets of encoding neurons with temporal codes is proposed in [5,39,41]. 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. A network of spiking neurons with AM capability is used to build a dynamic pattern recognition system [6].

AM of spatio-temporal data [7] allows the model to be trained on all temporal variables and recalled on part of them in both time or space.

The paper is organized as follows: Section 2 presents the background knowledge of SNN, NeuCube [11] and STAM [7]. Section 3 introduces the proposed PAMeT-SNN framework, which functional diagram is shown in Fig.1. Section 4 presents an experimental study using the method on trade time series data, and section 5 applies the method on a second case study time series data. Section 6 is the conclusion.

II. Spiking Neural Networks (SNN), the NeuCube Brain Inspired SNN Architecture and STAM

A. Spiking Neuron Models

In SNN, information is represented and processed as sequences of spikes, i.e., binary events at specified times. SNN departs 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 [8]-[17]. The Leaky integrate-and-fire (LIF) neuron model is adopted in many SNN systems (for a review, see [13]). 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 membrane potential u(t) of the neuron is shown in (1).

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

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

B. Spiking Learning Rules

1) Spike-Timing Dependent Plasticity (STDP)

The Spike-Timing Dependent Plasticity (STDP) learning rule is implemented [8] where the firing order of connected neurons determines the synaptic weight. If a pre-synaptic neuron fires first, before a post-synaptic neuron, then long-term potentiation (LTP) is established to strengthen the synapse weight. However, if a post-synaptic neuron activates first, a long-term depression (LTD) occurs, weakening the connection weight. Thus, the modification of the synapse (increase or decrease in weights) 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 SNNcube retains the connections as long-term memory. Then, if just part of the new information is inputted, a chain of activities would fire in the SNNcube based on established connections [9]. Thus, the NeuCube can be explored for learning long spatio-temporal patterns and utilized as associative memory and as a predictive system for event prediction when only some initial new input data is presented.

The STDP function is defined as in (2,3).

$$\Delta\omega = \begin{cases} +a \,.\, e^{\frac{t_{pre}-t_{post}}{\tau_+}} & \text{if } t_{pre} < t_{post} \\ -a \,.\, e^{\frac{t_{post}-t_{pre}}{\tau_-}} & \text{if } t_{pre} > t_{post} \end{cases} \quad (2,3)$$

where Δω is the change in weights; a is positive constant learning rate; t is time.

2) The rank order method (RO)

The rank order (RO) [10] learning rule allows for new connection weights are formed, depending on the order of the incoming spikes, and the number of spikes that follow the first spike, as in (4).

$$\omega_{i,j} = \alpha.mod^{order(j,i)} \pm d \quad (4)$$

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 update weight on first spike occurrence; $order(j,i)$ represents the order of the first spike at synapse j and it is zero for the first spike to neuron i then increases according to the input spike order at other synapses; d is the drift parameter that updates the connection weight on subsequent spikes.

C. The NeuCube SNN Architecture

The NeuCube architectural paradigm is inspired by the human brain and its ability to form AM [11]. It consists of: spike encoding module; 3D SNNcube module; SNN classifier/regressor; parameter optimization module. NeuCube learns from data and connects clusters of neurons to capture the

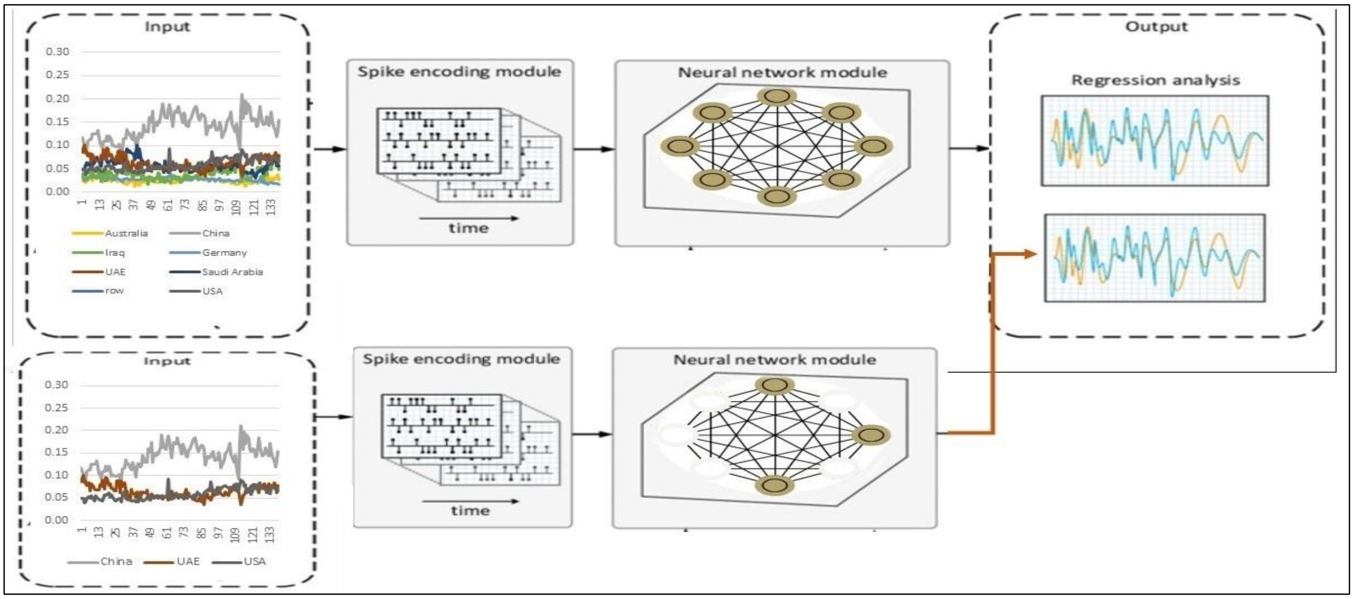


Fig. 1. The proposed PAMeT-SNN framework, consisting of: spike encoding module; 3D SNNcube; regression module, inspired by NeuCube [11] and tailored for the first case study trading data. The upper scheme is the training part of a full model and the lower is its recalling on smaller data set .

complex temporal relationships between input features of the time series data and to provide a more interpretable representation of the underlying dynamics of the time series in order to make a prediction when new input data is presented.

The NeuCube functioning includes the following algorithms:

1) Spike encoding of input signals

In the threshold-based encoding algorithm, excitatory (positive) and inhibitory (negative) spikes are generated based on substantial changes in the signal intensity over a certain threshold that is calculated. Encoded spikes are formulated only if variation in consecutive input values is different from the threshold (TH), which are then used as inputs to the spatially located neurons from the SNNcube module [13].

2) Model Initialization

The generated spikes are mapped to a predefined number of neurons located in the 3D-SNNcube. The connections between the neurons are initialized using the small-world connectivity (SWC) approach. 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 [9].

3) Unsupervised Learning Phase [13]

Using the STDP learning rule, a SNNcube is trained on the encoded samples. Some hyper-parameters should be defined, such as the neuron's potential leak rate, the neuron's refractory time after emitting the spike, the STDP learning rate for updating the connection's weights, the firing threshold for the neuron to generate a spike, the number of training iterations, and the long-distance probability.

4) Supervised Learning Phase

The computationally efficient dynamic evolving Spike Neural network (deSNN) is trained as an output classifier/regressor using labeled information associated with input samples [11].

When a new input vector is encoded as input spikes during the recall phase, the spiking pattern is transmitted to all newly generated neurons during the learning phase in the SNNcube. If an output neuron's membrane potential exceeds its threshold, neuron i generates an output spike at time t.

5) 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 [13].

D. Spatio-temporal associative memories (STAM)

The idea of using NeuCube for STAM was first introduced in [11]. In [7] some principles, definitions, and evaluation criteria of STAM are presented.

STAM is a system that is trained for classification or prediction on all available spatio-temporal data and their variables and recalled only on part of these variables and/or part of their temporal length. Two validation criteria are introduced for STAM in [7]:

- association accuracy, measuring how well a STAM system trained on all spatio-temporal data can be recalled of smaller part of the same data;
- generalization accuracy, where the above test is applied on a new spatio-temporal data.

In the next section we present the proposed PAMeT-SNN method and framework.

III. The Proposed PAMeT-SNN Method

The functional framework of PAMeT-SNN is presented in Fig.1. In this section we present the method and also illustrate it on the first case study data, which is fully investigated in section III.

The first case study data [23] is a time series trading data set that represents India's major trading partners, including China, Australia, Germany, Iraq, Saudi Arabia, United Arab Emirates, United States, and other countries as Rest of World

(ROW). In this model, the share of monthly imports as a proportion of total imports is used instead of the values of imports. The output variable in this case represents the next month share of Chinese imports to India.

As explained in section II, learning in the SNNcube is spatio-temporal, i.e., time series data is first spatially mapped into the structure of the SNNcube and then the local learning rule STDP is applied to the encoded into spike sequences data which changes the connectivity between neurons inside the SNNcube in space and time. To map time series data spatially into a 3D SNN model, first existing time series are analyzed in terms of their similarity, before and after spike encoding. Using the graph matching algorithm proposed in [9], similar variables are mapped to closer spiking neurons in a 3D SNN model (Fig. 2a).

Based on the spatial mapping of temporal variables and the unique feature of NeuCube for spatio-temporal learning, the main hypotheses addressed in the paper is: Once a PAMeT-SNN model is trained on a full scale of time series variables for prediction, it can generalize to partial time series variables, both in terms of number of variables used and their time length.

The rationale behind the hypothesis is the following. The SNNcube accommodates the time series similarity information first as spatial coordinates of the input vbariables. Then the SNNcube is trained on the time series data 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 (Fig. 2a).

Once a SNNcube 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 polychronization [15] and synfire [16].

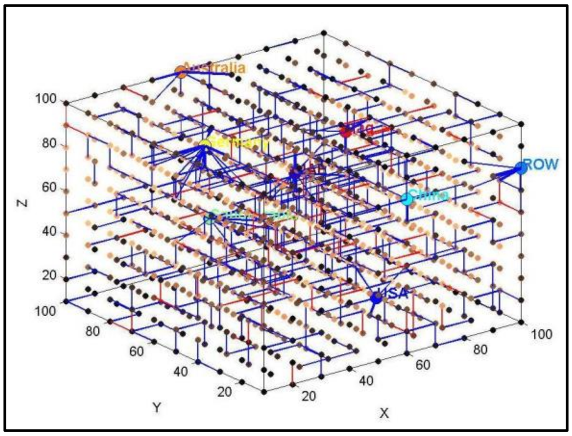
And these connections can be activated even for a shorter time of the temporal variables, rather than for the full time used in the training of the full model.

The research question now is: How to find the important variables K1 and their time T1 of measurement for recall of a fully trained model on K variables measured over time T, so that the prediction accuracy on the recalled time series data would not be affected? Can these variables be used as predictive markers? The complexity of the problem comes from the fact that here we deal with temporal variables, rather than with static vector-based data, and also from the fact that only few variables can be used for a recall of a model, trained on a full set. In this way some limitations of the traditional deep neural networks can be overcome [17].

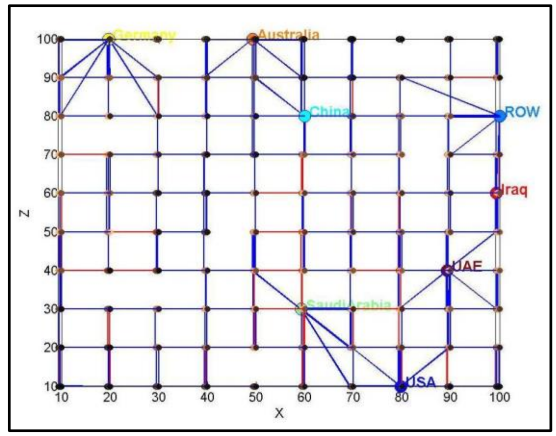
The proposed PAMeT-SNN methodology consists of the following procedures:

1. Defining the set of K time series variables for the prediction of a targeted output time series variable or a future event.
2. Encoding the K time series variables into spike sequences.
3. Spatially mapping the K input variables into the SNNcube using the graph mapping algorithm [9] (see Fig. 2a).
4. Training the 3D SNNcube with the STDP unsupervised learning and the deSNN output regressor with supervised learning.
5. Analyze the impact of the input variables in the SNNcube model through calculating a feature interaction network (FIN) as a graph of the number of spike exchange (information exchange) between the clusters of the input variables during learning [13]. The more spikes are exchanged between 2 variables, the more important they are for the predictive model.
6. Rank the importance of variables based on the information from step 5.
7. Remove lower ranked variables and recall the NeuCube model only on the left K1 variables, check the association and generalization accuracy.
8. Recall the model on the K1 variables, measured over time T1 < T and calculate the association and generalization accuracy.
9. Repeat step (8) for smaller time intervals until satisfactory accuracy.
10. Repeat steps (7), (8) and (9) to estimate the final number of important variables K1 and their time of measurement T1 that can be used to recall a NeuCube model without sacrificing the regression accuracy.
11. Evaluate the K1 variables as potential predicting markers according to the prediction problem in hand.

When smaller number of variables K1 is entered into a fully trained PAMeT-SNN model for a recall (step 8), the other variables are zeroed, so that they are represented by no spikes, meaning no changes. This is a significant difference between the PAMEeT-SNN and traditional neural networks, that makes the proposed model flexible in both space (variables) and time (their temporal length). When a PAMeT-SNN model, trained with full set of variables, is recalled on a smaller subset of them, the already created connections in the SNNcube are activated even with smaller number of inputs, if these connections represent strong association between the input variables (see Fig.8). In this respect, by zeroing an input variable during a recall process does not mean “ignoring” its impact on the output as this variable may have a strong connection with the output variable, learned in the full model. This is a biologically plausible principle [40].



(2a)



(2b)

Fig. 2a. Spatial mapping of 8 time series variables (country import to India from the case study data [23]) into a SNNcube of 1,000 neurons with the use a graph matching algorithm [7] and connectivity between neurons after unsupervised training of the SNNcube, where connections represent spatio-temporal interaction between input variables. Fig. 2b. represents the (x, z) projection of the SNNcube connectivity. Blue lines are positive connections (excitatory), while red lines are the evolved negative connections (inhibitory).

IV. PAMeT-SNN Model on Case Study 1 Trade Data

A. Case Study on Time Series Trade Imports Data

Dataset Description

The trading case study data was briefly introduced in section III. In 2022, India has 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 [18] [19] [20]. India's imports in 2020 accounted for 2.4 percent 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 [21] [22].

A PAMeT-SNN model is developed here on this case study, involving predictive modeling of trade data, particularly when limited features are presented on recall. From January 2011 to July 2022, 139 observations of monthly imports of goods were obtained from the United Nations Comtrade [23].

B. Dataset Pre-processing

Using a sliding window of 12 months, one data point at a time, 127 overlapping samples have been generated from the original dataset. The 8 input features/variables are the monthly import to India from each of the 8 countries, while the target prediting feature is the next month import from China as the biggest importer to India.

C. Dataset Modeling

Conforming to the PAMeT-SNN method from section III, the developed here model encodes spikes using the threshold-based representation (TBR) encoding algorithm. The TBR generates positive and negative spike sequences in response to an increase or decrease in the real value of two consecutive import values from the input time series (Fig.3).

The advantage of using the PAMeT-SNN model with the TBR encoding algorithm is that it can deal with noisy data, ignoring small perturbations in it. The algorithm is suitable for trade data analysis as it focuses solely on identifying differences between successive temporal characteristics [25].

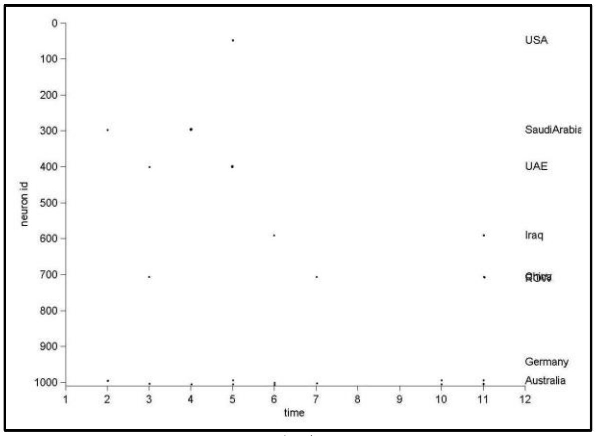
In this model, the spike threshold is set at 0.5, and the generated spikes are initially mapped to the randomly connected LIF-based neurons of the NeuCube using a small world (SW) connectivity rule with a radius of 2.5. STDP learning is used in an unsupervised learning stage to capture spatio-temporal associations from encoded inputs. Here the used STDP learning rate is 0.01 and the firing threshold of the LIF neurons is set to 0.5. When this threshold is reached, the neuron emits a spike, and its membrane potential is reset to zero for the duration of its refractory time, which is set at 6 units. The membrane potential leaks between spikes at a potential leak rate of 0.002.

The dynamic evolving deSNN regressor is utilized in the supervised mode, with each output neuron associated with a single training sample that is connected to every other neuron in the SNNcube. The connections between connected neurons [i,j] are initialised using the Rank-Order (RO) method of the first incoming spike with the modulation factor (Mod) set to 0.8. The spike-driven synaptic plasticity (SDSP) learning rule adjusts these connections with a drift value $\delta = 0.005$, increasing their weight when spikes arrive at next time points and decreasing it if no spikes occur [11].

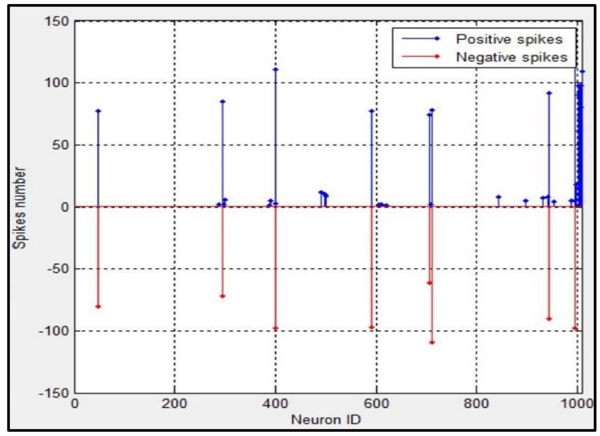
D. Experimental Results, Analysis, and Visualization

The set of samples was split in half so that 50% of the data were used for training, and the other 50% were used for incremental learning and validating the model. After the unsupervised learning phase is completed, the connections between the input neurons in the trained SNNcube are displayed in Fig. 2a. Positive (excitatory) connections between neurons are shown as blue lines, and negative (inhibitory) connections are represented in red. Fig. 2b. represents a cross-section projection of the 3D SNNcube offering a clear view of the inner connections.

A spike raster plot in Fig. 3a is an example representing spiking activity of all input neurons over for one sample of 12 months, where each dot corresponds to the occurrence of a spike from a particular input neuron. Fig. 3b shows the amount of positive and negative spikes being emitted by each neuron during the learning stage.



(3a)



(3b)

Fig. 3a. A spike raster plot provides a visual representation of the spiking activity across all 1000 neurons during learning of one sample of 12 time points, where each dot corresponds to the occurrence of a spike at 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.

The learned interactions between the input neurons that represent the trading partners' imports are illustrated by the feature interaction network (FIN) graph in Fig. 4a. The influence of activity between trading partners is represented by connected straight lines. The denser the connection, the greater the effect between the partners. Fig.4b shows the average spike interaction between the clusters around the input variables. In this graphic representation, China-ROW corridor shows a strong influence between each other.

During unsupervised STDP learning in the SNNcube, spikes are transmitted across synapses between neurons, resulting in changes to the connection weights. Fig. 5a shows the clusters created around each input neurons and Fig.5b shows the size of these clusters. The larger the size, the more impact this input variable has on the model.

Once a full PAMeT-SNN model is created with the use of all K temporal variables and time series data available of length T, the model can be recalled using a smaller number of K1 < K variables, measured at a shorter times T1<T, which is demonstrated in the next sub-section.

E. Using the PAMeT-SNN to predict future imports with a small number of input trade time series variables at shorter times

The PAMeT-SNN model here aims to predict India's imports from China for the forthcoming time period using an incomplete dataset of independent features after a PAMeT-SNN model is created using eight time series variables representing imports from Australia, China, Germany, Iraq, Saudi Arabia, the United Arab Emirates, the United States, and other countries.

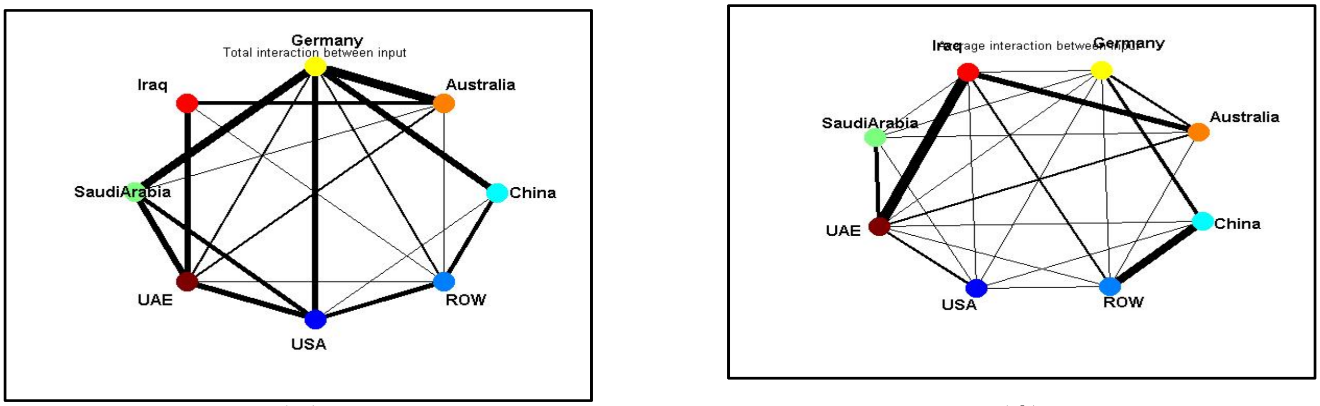
Using a graph mapping algorithm, the K-selected time series variables are encoded as spike sequences and mapped into the 3D SNNcube (Fig.2a). Following unsupervised learning with STDP and supervised learning to train the deSNN, the proposed algorithm learned and memorized all time series samples for training and relationships between the 8 variables in the model.

The experiments involved an iterative process to recall the model using reduced sets of input variables in order to predict the target variable for the next time period. The recall process is repeated for smaller data sets (K1 < K) until a satisfactory level of accuracy is attained. For simplicity, the time interval T1 is set to 1 (T1 = 1) out of the total time-frame of T = 12.

Through this iterative process, the final number of important variables (K1) is estimated for a given measurement time (T1=1). Table 1 shows the actual Chinese imports (when K=8) as well as a number of predicted values based on the results of several recall procedures based on various feature availability scenarios. It demonstrates that K1 = 3 is the best scenario for predicting India's imports from China when only the U.A.E., U.S.A., and historical trends of China are provided. Consequently, it can be considered a potential predictive marker with a minimum error.

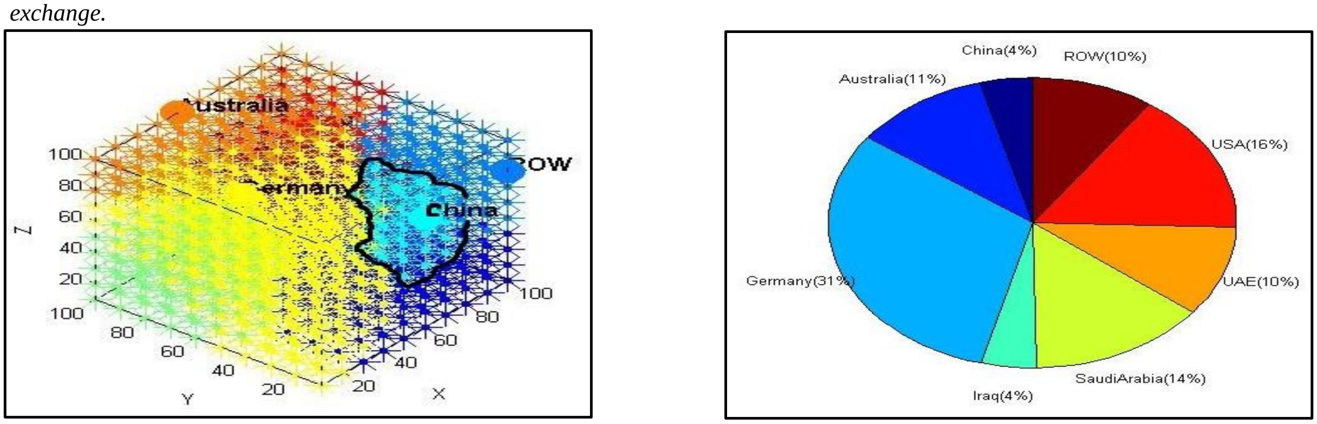
The PAMeT-SNN model is able to activate connections based on input variables in order to retrieve stored patterns or memories and then recall related patterns even when only a subset of input variables is provided. The PAMeT-SNN model effectively preserves associations as spatio-temporal connections between neurons and retains its initial connections that were established during the learning phase when recalling the model on a subset of input variables. The model adeptly retrieves patterns associated with partially connected input features and demonstrates a remarkable capacity for precise predictions. Notably, the dissimilarity between the predicted import patterns of China, obtained using the complete input dataset (Fig. 6a) and the reduced input dataset (Fig. 6b), remains minimal.

Fig.7 shows the predicted and the actual values of the import from China when only the input variables are used for a reduced time T=1 with an overall RMSE of 0.02.



(4a) *(4b)*

Fig. 4a. Total information exchanged between the neuronal clusters of input variables; the thicker the lines, the more spikes are exchanged between the clusters, meaning a temporal association/correlation of changes in the trade. Fig 4b. Average information exchange.



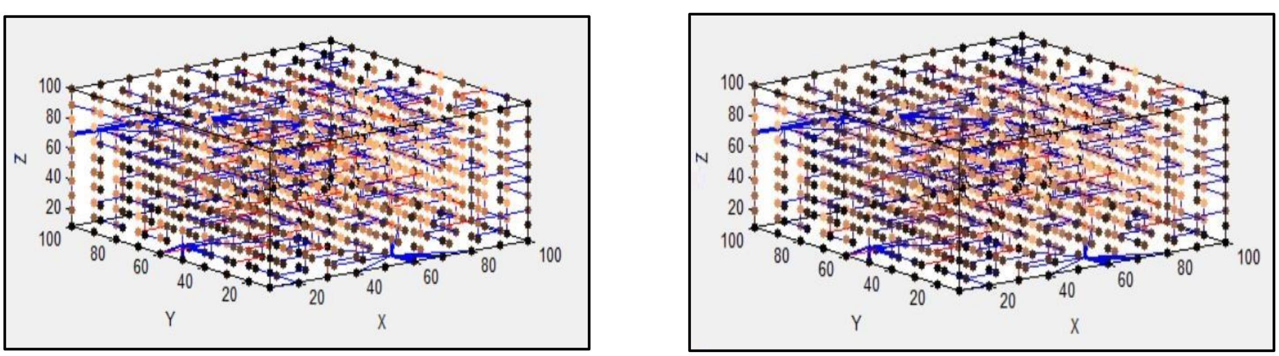
(5a) *(5b)*

Fig.5a. Neuronal clusters created through unsupervised learning in the SNNcube. Fig. 5b. Cluster proportion: larger clusters represent more impact of the input vbariable on the the model. .

TABLE I

THE PREDICTED PATTERN OF INDIA'S IMPORTS FROM CHINA

No. of Available Input Variables	Imports from China *[$B]*	Type	Prediction Error: Value[K] - value[K1]	Names of the input variables K1 for time T1=1 to recall the model
K = 8	0.154			Australia, China, Germany, Iraq, Saudi Arabia, UAE, USA, ROW
K1 = 7	0.148	PAMeT predicted	0.006	Australia, China, Germany, Iraq, Saudi Arabia, UAE, USA
K1 = 6	0.147	PAMeT predicted	0.007	Australia, China, Iraq, Saudi Arabia, UAE, USA
K1 = 6	0.134	PAMeT predicted	0.020	China, Iraq, Saudi Arabia, UAE, USA
K1 = 4	0.147	PAMeT predicted	0.007	Australia, China, Iraq, Saudi Arabia, USA,
K1 = 3	0.153	PAMeT predicted	**0.001**	China, UAE, USA
K1 = 2	0.172	PAMeT predicted	0.018	Australia, China
K1 = 1	0.162	PAMeT predicted	0.008	China



(a) (b)

Fig. 6a. Activated connections when all 8 variables are used for a recall of a fully trained model on the K=8 variables for T=12 data points. Fig.6b. Activated connections when only UAE, USA, and China's (K1=3) time series are used to recall the model for T1=1.

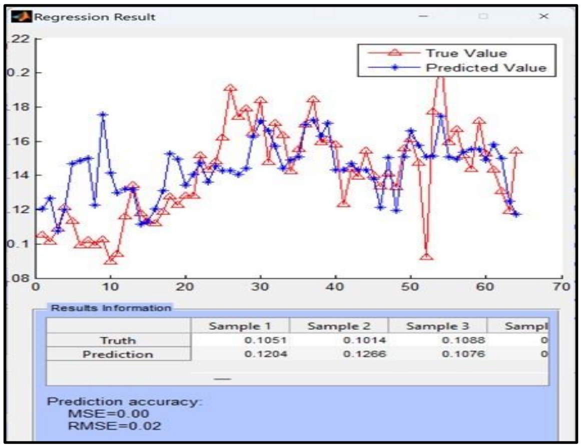


FIG.7. PREDICTED VS ACTUAL VALUES OF THE IMPORT FROM CHINA TO INDIA WHEN THE FULL PAMET-SNN MODEL IS RECALLED WITH THE USE OF K1=3 INPUT VARIABLES FOR A RECALL TIME OF T1=1.

V. PAMeT-SNN ON A CASE STUDY 2 DATA

A. Case Study on Time Series Commodity Price

Expanding the scope of this research and aligning it with diverse domains in trade, economics, and finance, a second case study on commodity market prices was conducted to demonstrate the adaptability of the proposed PAMeT-SNN method.

B. Dataset Description

Complex interaction of economic forces contributes to the dynamic nature of commodity markets. According to a recent assessment by the World Bank [25], the energy sector encountered a notable increase, with energy prices escalating by 6% in July 2023. For this case study, market prices of eight commodities have been downloaded from the International Monetary Fund (IMF) Commodity Portal [27][26]. The data spans from January 2010 to May 2023, with a total of 161 observations of the monthly market prices of the eight selected commodities (Table II).

TABLE II
THE SELECTED COMMODITIES AS SPATIAL 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

C. Dataset Pre-processing

Utilizing a sliding window approach with a step size of 1, a total of 149 overlapping samples have been generated from the original dataset, each of them represented as 8 time series of length T=12 time points.

D. Dataset Modeling

The generated samples were split in half, where 50% of the samples was used for training, and the remaining half for incremental learning and validating the model. The proposed PAMeT-SNN model encodes spikes using the threshold-based representation (TBR) algorithm with a spike threshold of 0.5 [11]. Initially, the generated spikes are spatially mapped into the NeuCube using the graph matching algorithm [9] with a small world (SW) connectivity radius of 2.5. During unsupervised learning, the following NeuCube hyperparameters were set: STDP learning rate was set to 0.01, potential leak rate was set to 0.002, firing threshold was set to 0.5, and refractory time was set to 6 units. The modulation factor was set to 0.95 with a drift parameter of 0.03 during the supervised mode.

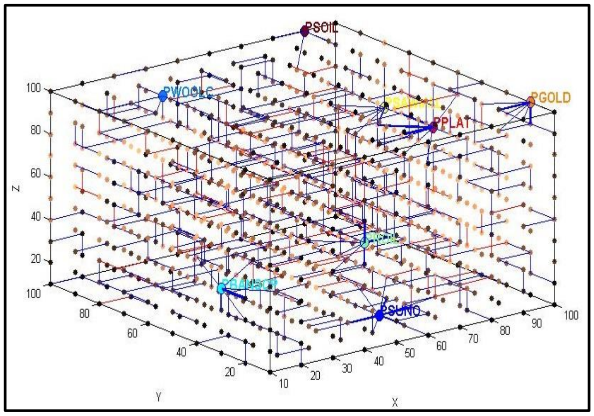
E. Experimental Results, Analysis, and Visualization

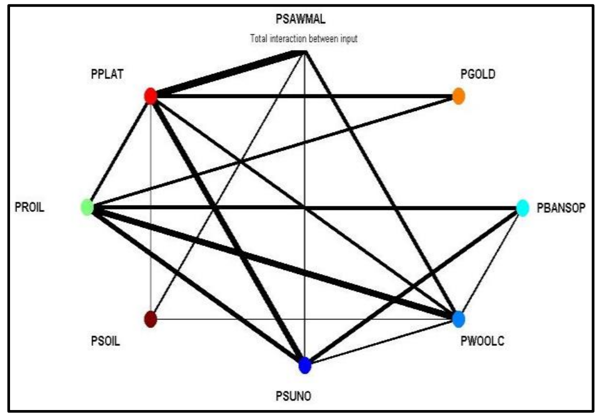
After the spatial mapping of temporal variables according to the similarity of the time series as spatial coordinates, the spike-time dependent plasticity (STDP) learning is performed on the encoded spikes. Consequently, the connection weights between neurons reflect the temporal relationships between the input commodities (Fig. 8a). The similarity between the Platinum and Gold, as precious metals, are spatially mapped next to each other in the SNNcube.

The feature interaction network (FIN) graph in Fig. 8b shows the learned interactions between the input neurons that represent the commodity market prices.

According to the FIN graph, the analyzed feature, ‘Platinum’, has the highest activity with other features. There is a strong direct influence with PGOLD, PSUNO, PSAWMAL, and a modest relationship with PWOOLC, PROIL, and PSOIL. PGOLD, the other precious metal, is strongly connected with PPLAT and PROIL.

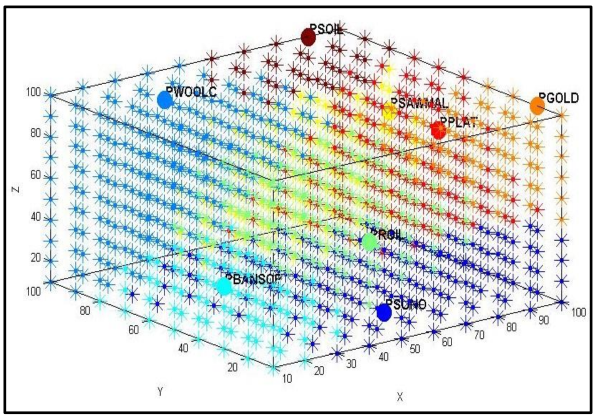
Custers in the SNNcube around the input variables are depicted in Fig. 9a, where Platinum’s cluster accounts for 13% of all spike activity. The accuracy achieved by the PAMeT-SNN model was 84%. Subsequently, the model was evaluated by performing 2-fold, 3-fold, and 4-fold cross-validation. The latter provided the highest level of accuracy, 93% (Fig. 9b).

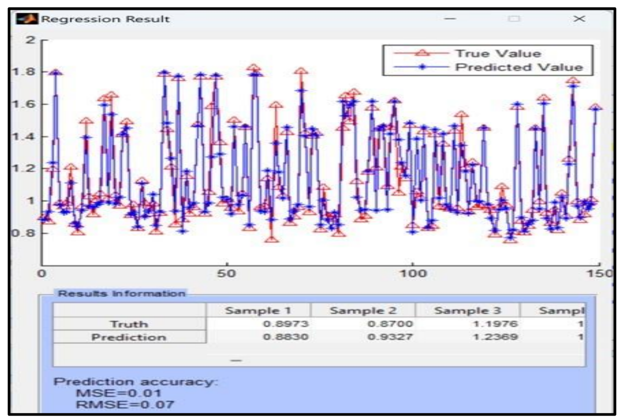




(9a) *(9b)*

Fig. 8a. The connectivity in SNNcube during unsupervised learning on market prices K= 8 commodities. Fig. 8b. Total information exchanged between the neuronal clusters of commodities, weighted by the thickness of the connections.





(10a) *(10b)*

Fig.9a. Neuronal clusters created through unsupervised clustering in a SNNcube, where the Platinum's cluster accounts for 13% of total spike activity. Fig. 9b. Regression results with a prediction accuracy is 93% after 4-fold cross validation with all 8 variables used..

F. Using the PAMeT-SNN to predict future price with a smaller number of input commodity time series variables

The efficiency of the PAMeT-SNN model in capturing and forecasting complex dynamics in the commodities market is validated by its application for analyzing and predicting commodity market prices. This case study applies many experiments on the PAMeT-SNN method with the objective to estimate the future market price of the Platinum commodity utilizing an incomplete dataset of independent features.

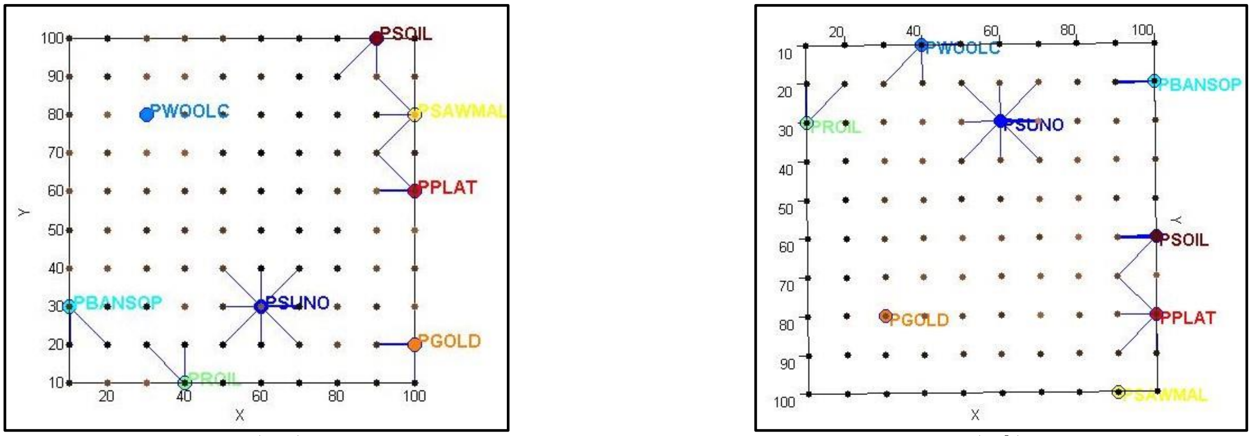
In accordance with the methodology outlined in section III, the PAMeT-SNN model was originally employed for the whole input stream (K = 8). Subsequently, the experiments involved a repeating procedure whereby the model was recalled by using reduced datasets of input variables. The recall procedure is iterated for subsets of data that are smaller in size (K1 < K) until a desirable degree of precision is achieved.

According to the feature interaction network (FIN) graph (Fig. 8b), it can be observed that variables exhibiting a higher number of spikes exchanged, are indicated with thick connections, and deemed to possess more significance in terms of their predictive capabilities throughout the whole sample. The time period T1 is set to 1 out of whole timeframe T = 12.

Table III demonstrates that K1 = 4 is the best option for predicting the market price of platinum when only the PBANSOP, PSAWMAL, PSOIL, and PPLAT historical values are available. Consequently, it can be regarded a potential predictive marker with a minimum error rate of 4.2%.

In contrast, the traditional linear regression analysis of univariate variables predicts a 32% error in the market price of platinum based solely on their historical trends, as shown in Table III's final row.

The PAMeT-SNN model successfully maintains associations by preserving the spatio-temporal connections between neurons. Furthermore, when recalling the model on a subset of input variables, it retains the initial connections established during the learning phase (Fig. 10a, b). When all analyzed variables (K=8) are present in the input stream, the model effectively captures the complexities of commodity price dynamics and depicts the model's full connectivity (Fig. 10a). The displayed connections have a threshold weight of 0.1. During recall, where only a subset of input variables is available (K1 = 4), certain connections are not present (Fig. 10b), but that does not prevent an accurate prediction.



(11a) *(11b)*

Fig. 10a. The connectivity evolution in NeuCube during global training on prices data recorded from the 8 commodities.
Fig. 10b. The connectivity during local recall on prices recorded from only 4 commodities (PBANSOP, PSAWMAL, PPLAT, PSOIL).

TABLE III
THE PREDICTED MARKET PRICE OF PLATINUM COMMODITY WITH REDUCED INPUT DATASETS

No. of Available Input Variables	Imports from China *[$B]*	Type	Prediction Error: Value[K1] - value[K]	Names of the available input variables to recall the model
K = 8	1.0590	Real value	-	PBANSOP,PGOLD,PSAWMAL,PPLAT,PROIL,PSOIL,PSUNO,PWOOLC
K1 = 7	1.5148	PAMeT predicted	+0.456	PBANSOP,PGOLD,PSAWMAL,PPLAT,PROIL,PSOIL,PWOOLC
K1 = 6	1.3744	PAMeT predicted	+0.315	PBANSOP,PSAWMAL,PPLAT,PROIL,PSOIL,PWOOLC
K1 = 5	0.8996	PAMeT predicted	-0.160	PBANSOP,PSAWMAL,PPLAT,PSOIL,PWOOLC
K1 = 4	1.1015	PAMeT predicted	**+0.042**	PBANSOP,PSAWMAL,PPLAT,PSOIL
K1 = 3	1.3043	PAMeT predicted	+0.245	PSAWMAL,PPLAT,PSOIL
K1 = 2	1.2064	PAMeT predicted	+0.147	PPLAT,PROIL
K1 = 1	0.9827	PAMeT predicted	-0.076	PPLAT
K1 = 8	0.7415	Linear Reg. predicted	-0.318	PBANSOP,PGOLD,PSAWMAL,PPLAT,PROIL,PSOIL,PSUNO,PWOOLC

This distinctive behavior of the PAMeT-SNN model to make good predictions with incomplete input allows it to recall relevant information accurately even when operating with a reduced set of variables without compromising the model's accuracy. Thus, PAMeT-SNN represents a paradigm shift in the field of artificial intelligence.

VI. DISCUSSION AND CONCLUSION

PAMeT-SNN model offers an effective approach for time series analysis and prediction. Its ability to learn and recall complicated temporal patterns qualifies it for a wide range of applications in various domains such as finance, engineering, and healthcare.

The proposed here method can be used to extract temporal fuzzy rules, to be used for a comparison between fully trained and partially recalled PAMeT, adding to the explainability of the model [27].

In [28] [29], time series environmental data collected over 40 days, such as pollution, temperature, wind, solar eruption and others, are used to predict individual stroke occurrence. The proposed PAMeT-SNN can be applied to make on-line predictions of individual stroke prediction based only on few of these variables and a shorter time, saving human lives.

In [30] an earthquake prediction system is described that uses 100 days seismic spatio-temporal data to predict an earthquake event several hours ahead. Here a PAMeT-SNN model can be applied for an early event prediction based on shorter time series data and smaller number of seismic input variables.

In [31], London city pollution prediction system is described and in [32] a similar pollution prediction system is presented for the areas of Beijing and Shanghai. They use a large number of spatially located sensors to predict pollution several hours ahead using their time series measurements. PAMeT-SNN model can be applied for an early prediction based on shorter time series data and smaller number of pollution sensors.

In [33], different methods were discussed for predicting and modeling long time series data on Bulgarian petroleum oil imports from 19 key trading partners in order to identify abnormal patterns over time. The suggested PAMeT-SNN can be used to forecast a crucial commodity based on fewer factors, which is especially useful when data is scarce during crises and pandemics.

In [34], financial time series data and online news were integrated to improve forecast accuracy and data interpretation. The proposed PAMeT-SNN will be applied to forecast a stock index using news data and reduced time series.

PAMeT-SNN is suitable for wider range of applications where other methods were previously applied [35-38].

In summary, the paper offers a new trend in AI, where instead of creating and recalling many models for the same problem, each using same set of temporal variables for training and recall, but different variables across the models, as it is the case with the deep neural networks, here one

PAMeT-SNN is created globally on a large number of time series variables and recalled and updated many times locally on smaller subsets of variables. This introduces a new direction for AI of a *global* model training and a *local* model recall.

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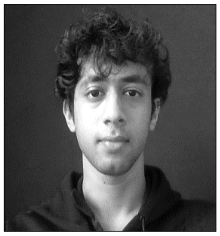

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