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Hybrid Neuro-Symbolic Learning Models Integrating Symbolic Reasoning And Data-Driven Approaches

Amit Sharma¹, Ganesh D², Aditee Mattoo³, Naresh Kaushik⁴, Nivetha N⁵, Monisha J⁶, Indiaminova Gavkhar Nuriddinovna⁷

¹ Associate Professor, Department of Computer Science & Engineering, Vivekananda Global University, Jaipur, India. Email: sharma.amit@vgu.ac.in, ORCID: 0000-0001-9825-3978

² Professor, Department of CS & IT, JAIN (Deemed-to-be University), Bengaluru, Karnataka, India. Email: d.ganesh@jainuniversity.ac.in, ORCID: 0000-0002-4220-3821

³ Assistant Professor, Department of Computer Science and Engineering, Noida Institute of Engineering and Technology, Greater Noida, Uttar Pradesh, India. Email: aditeemattoo@niet.co.in, ORCID: 0000-0002-5978-5741

⁴ Assistant Professor, Department of uGDX School of Technology, Atlas SkillTech University, Mumbai, Maharashtra, India. Email: naresh.kaushik@atlasuniversity.edu.in, ORCID: 0000-0002-9896-4662

⁵ Assistant Professor, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: nivethan@maher.ac.in

⁶ Assistant Professor, Department of Management Studies, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: jmonishamba@maher.ac.in

⁷ PhD, Docent, Department of Children Dentistry, Samarkand State Medical University, Samarkand, Uzbekistan. Email: gavhar3003@mail.ru, ORCID: 0009-0001-3500-1041

Abstract

Timely, reliable, and interpretable decision-making is essential in dynamic, data-intensive environments with uncertainty and evolving behavior. Neural networks offer strong prediction but limited interpretability, while symbolic systems ensure logic but lack scalability and adaptability. This research proposes an Explainable AI (XAI) using a Hybrid Neuro-Symbolic Learning Model for dynamic environments by integrating data-driven learning with rule-based reasoning. The Dynamic Transient Search Optimized Deep Neural Network (DTSO-DNN) neural component learns deep latent representations from heterogeneous inputs such as sensor and contextual data. DTSO optimizes DNN training by searching for optimal weights and parameters, improving convergence, avoiding local minima, and increasing stability in dynamic data environments. DNN learns complex nonlinear patterns from data and performs feature extraction and prediction from heterogeneous inputs. Data is taken from the Neuro-Symbolic Decision Dataset with sensor features and labels, normalized using Z-score for standardization, and features are extracted using Discrete Wavelet Transform (DWT) to capture temporal patterns and support symbolic reasoning for improved fault diagnosis. Shapley Additive Explanations (SHAP) is used as a post-hoc explainability technique to quantify the contribution of each input feature to individual model predictions in order to improve interpretability. Total Harmonic Distortion (38.4%), Line Outage Recovery Time (2.0 min), Distributed Energy Resource Failure Recovery Time (1.8 min), Load Shedding (39.3 kWh), Renewable Energy Utilization (97.9%), Renewable Curtailment (4.5%), and Computation Time (0.30s per 5-minute interval) are among the experimental results that show the suggested model achieves strong performance and were implemented in MATLAB. When compared to independent neural or symbolic methods, these findings demonstrate increased accuracy, robustness, and explainability.

Keyword: Hybrid Neuro-Symbolic Learning, Neuro-Symbolic AI, Symbolic Reasoning, Data-Driven Learning, Knowledge Graphs, Deep learning

Introduction

Neuro-symbolic AI, which involves combining symbolic AI's explainability with the flexibility of the neural network, represents the newest AI innovation in AI development [1]. Intelligent technologies' design for aiding decision-making under uncertainty and limited and constantly changing information is becoming more common.

This is due to an increasing interest in developing reliable, explainable, and effective intelligent tools. There has been an evident increase in interest in researching hybrid intelligent systems aimed at implementing learning, inference, and flexibility within a single framework [2, 3, 4]. Deep learning (DL), a branch of machine learning, extracts high-level features from large, complex datasets using multi-layer neural networks. DL models are extensively utilized in many different disciplines for perception, pattern recognition, and predictive analytics. These methods have greatly enhanced performance in fields like autonomous systems, healthcare, and finance [5-7]. By offering explanations for model predictions that are intelligible to humans, XAI improves the transparency of AI systems. Through feature attribution and reasoning techniques, it aids in the interpretation of intricate Deep Learning (DL) conclusions, enhancing dependability and trust in crucial applications. However, there are still some disadvantages to using the current techniques. The application of deep learning algorithms in safety-critical domains such as medicine, self-driving cars, and financial services is restricted due to their tendency to function as black boxes, making them difficult to understand and explain. Although symbolic AI provides transparent reasoning based on rules, it cannot scale up or be adapted for large and changing databases. Moreover, both techniques fail to deal effectively with uncertainty, noise, and present decision-making [8-10].

Research objective: The intention of the research is a Hybrid Neuro-Symbolic Learning Model, a composite of symbolic reasoning and DTSO-DNN, to allow dependable, interpretable, and logically coherent decision-making of diverse information under difficult, dynamic, and mission-critical circumstances.

Related Works

Table 1 summarizes literature on neuro-symbolic AI methods, highlighting improved reasoning, accuracy, and explainability, while challenges remain in scalability, computational complexity, world deployment, and adaptability across dynamic environments.

Table 1: previous research objective, method, result and limits

Ref	Objective	Method	Results	Limitations
[11]	Adaptive hybrid reasoning system	KG + Neural Representation Learning (NRL) + Symbolic Inference (SI)	Improved accuracy, flexibility	Integration complexity limits scale
[12]	Lightweight neuro-symbolic learning	Semantic Loss Function (SLF) constraints	Better recognition accuracy	Reduced interpretability, flexibility
[13]	Integrate symbolic reasoning with the pattern recognition capabilities of neural networks.	Integrate learning and reasoning for robust AI systems	Create AI systems with explainable inference and strong generalization.	Struggles with complex, large-scale data integration.
[14]	Integrate NSAI with ML/DL for mineral prediction	Combine DL with symbolic reasoning.	Enhance prediction accuracy and decision-making.	Challenges in domain expertise integration and biases
[15]	Reliable complex decision system	KG + RBL	Better adaptability, accuracy	High cost and integration complexity
[16]	Optimize microgrid energy using neuro-symbolic AI.	Neuro-Symbolic Artificial Intelligence (NSAI)	Reduced costs, improved efficiency, and power quality.	Simulation-based; real-world scalability not tested.

Methodology

The Neuro-Symbolic Decision Dataset, which contains diverse data, such as sensor measurements and contextual data, is employed to conduct experiments. The process of z-score normalization is applied for handling noise as well as missing values. Additionally, the DWT is applied to extract features. Although knowledge graphs and rule-based reasoning play an important role in symbolic reasoning for ensuring logical consistency, DTSO-DNN and SHAP are adopted for finding patterns and are illustrated in Figure 1.

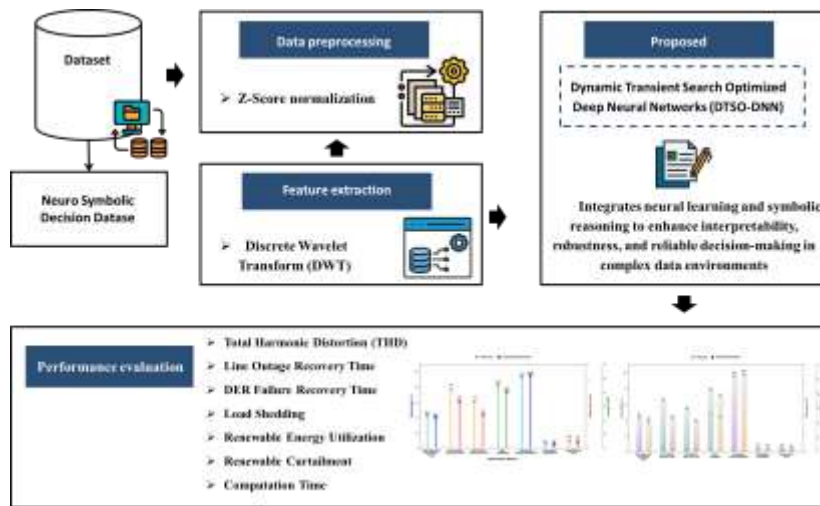


Figure 1: Hybrid Neuro-Symbolic Framework Integrating DTSO-DNN for Robust and Explainable AI

Data Collection

This dataset is an ensemble of 7000 data samples that can be used to use hybrid neuro-symbolic learning approaches to make explainable decisions in dynamic systems. Hybrid learning is based on the Neuro-Symbolic Decision Dataset, which includes multivariate sensor signals, contextual data, symbolic rules, and knowledge graphs. Because the provided dataset contains all dynamic system behaviors, environmental variables, and fault histories, the decision-making process is consistent and interpretable. The DTSO-DNN hybrid learning approach enables data-driven neural learning and symbolic reasoning by leveraging all those features.

Kaggle Source: <https://www.kaggle.com/datasets/colabsss/neuro-symbolic-decision-dataset>

Data feature exploration Analysis: Figure 2 shows an explainable decision-making process in dynamic and data-rich settings using neuro-symbolic learning systems. Figure 2(a) displays the correlation between various sensor variables, showing patterns that are significant for operational analysis. Figure 2(b) displays the distribution of temperatures and pressures with symbolic and contextual factors, illustrating how a combination of data and rules can make decisions more explainable, consistent, and reliable. The application of explainable decision-making within dynamic data-rich systems through hybrid neuro-symbolic learning. Figure 2(c) shows the mapping of multi-class operational states – Critical, Warning, and Normal, illustrating interpretability within decision making. Figure 2(d) demonstrates pressure distribution of the system, showing the importance of sensor information, contextual information, and symbolic knowledge in reasoning.

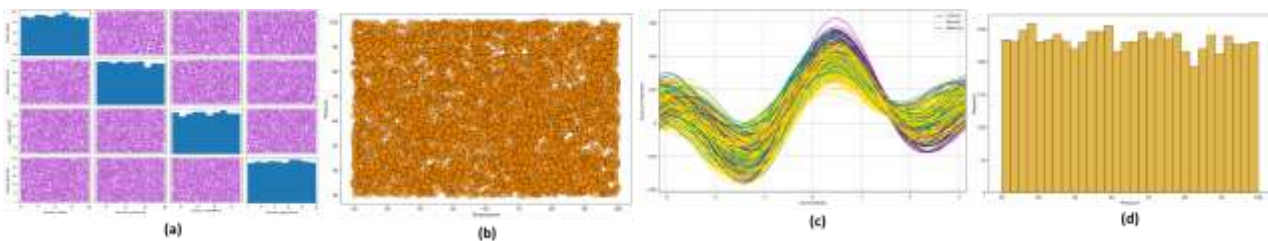


Figure 2: Neuro-Symbolic Feature Analysis for Explainable Decision-Making (a) sensor correlation, (b) temperature-pressure distribution, (c) multiclass feature projection, and (d) pressure distribution

3.2 Data preprocessing using Z-Score normalization

Data preprocessing transforms diverse forms of data to make them ready for analysis by arranging the data in an organized and understandable form. Z-Score normalization makes all sensor values, context values, and symbolic values are brought to a common scale. This leads to better pattern identification, accurate reasoning, and informed decisions; in other words, it ensures explainable AI.

$$(\sigma) = \sqrt{\frac{\sum_{j=1}^m (E_j - \mu_j)^2}{m}} \tag{1}$$

Equation (1) presents σ is the standard deviation of feature weights, σ, E_j is the j th feature weight/value, μ_j means value of the j -th feature, m is the total number of features, $\sum_{j=1}^m$ is the sum over all features.

$$Z - score(LT) = \frac{\ln(E_{ji}) - \ln(\mu_j)}{\sigma[\ln(E_j)]} \tag{2}$$

In Equation (2), $Z - score(LT)$ is the Z-score value after log transformation, μ_j mean of the j -th feature values, E_j is the values of the j -th feature, \ln is the natural logarithm, E_{ji} value of the j -th feature for the i -th sample, used to stabilize variance and lessen skewness, $\sigma(\ln(E_j))$ standard deviation of log-transformed feature values.

$$(Z - score)_K = \frac{(K_{Th} - \mu)}{\sigma} \tag{3}$$

Equation (3), $(Z - score)_K$ the normalized (Z-score) value of the K, K_{Th} threshold or observed feature value (raw input), μ mean of the feature distribution, σ mean standard deviation of the feature distribution.

$$(Z - score)_V = \frac{(V_{Th} - \mu)}{\sigma} \tag{4}$$

Equation (4) represents $(Z - score)_V$ mean Z-score normalized value of variable V, V_{Th} is the observed/threshold raw value of feature V, μ mean of the feature distribution, σ is the standard deviation of the feature distribution.

3.3 Feature extraction using Discrete Wavelet Transform (DWT)

The process helps in detecting faults in complex and data-intensive systems through the use of deep learning, to extract high-level features, and symbolic reasoning, to ensure consistent results. Extraction of features also be done using DWT, which involves the decomposition of time-series data into various frequency components. Advantages associated with this approach include consistency and reliability in making decisions and contributing to the development of neuro-symbolic hybrid artificial intelligence.

$$\psi(i, l)(s) = \frac{1}{\sqrt{2^i}} \psi\left(\frac{(s - l2^i)}{2^i}\right) \tag{5}$$

In Equation (5), ψ is the mother wavelet function, the basic building block of all wavelets and l is the scale index, l is the translation index and s is the continuous input variable (time or space), where the wavelet is evaluated, $\psi(i, l)(s)$ is the wavelet function at scale i and translation l , evaluated at position s and $\frac{1}{\sqrt{2^i}}$ normalization factor, $\left(\frac{(s - l2^i)}{2^i}\right)$ is the scaled and shifted argument of the mother wavelet of $(s - l2^i)$ is the shifts the wavelet to the correct position l . Division by 2^i scales (compresses or stretches) the wavelet according to the scale i .

$$\gamma_{i,l} = - \int_{-\infty}^{\infty} w(s) \frac{1}{\sqrt{2^i}} \psi\left(\frac{(s - l2^i)}{2^i}\right) dt \tag{6}$$

In Equation (6), $\gamma_{i,l}$ is the wavelet coefficient at scale i and translation l , Represents the how much the wavelet $\psi_{i,l}$ “matches” the signal $w(s)$ at that location and scale and $-$ negative sign, $(s - l2^i)$ is the separation between the signal point s and the wavelet’s center, which is shifted and scaled. The term provides the capability for the wavelet to move, or slide, around the signal with varying scale sizes. $\int_{-\infty}^{\infty} dt$ Integral over the entire domain of the signal, Measures the total “overlap” between the signal $w(s)$ and the scaled/shifted wavelet $\psi_{i,l}$ and $w(s)$ is the input signal being analyzed.

$$z_{low}[m] = (w * h)[m] = \sum_{l=-\infty}^{\infty} w[l]h[2m - l] \tag{7}$$

In Equation (7), $z_{low}[m]$ represents the low-frequency (approximation) coefficient at sample $m, w[l]$ input discrete signal, indexed by $l, (w * h)$ simply denotes the convolution operation between two signals w and h , The symbol $*$ denotes the convolution operation, $\sum_{l=-\infty}^{\infty} w[l]h[2m - l]$. Flip the filter, h and slides it over the signal w . Multiply corresponding entries and sum them \rightarrow gives the convolution result. Sample the result at every other point (due to $2m$) \rightarrow down sampling.

$$z_{high}[m] = (w * h)[m] = \sum_{l=-\infty}^{\infty} w[l]g[2m - l] \tag{8}$$

In Equation (8), $z_{\text{high}}[m]$ represents the high-frequency (detail) coefficient at sample m and $g[2m - 1]$, the high-pass filter (wavelet filter). Designed to pass high-frequency components and attenuate low-frequency (smooth) parts.

Hybrid Neuro-Symbolic Learning Models Integrating Symbolic Reasoning using DTSO-DNN

The proposed Hybrid Neuro-Symbolic Learning Model, DTSO-DNN, is employed to improve prediction accuracy, faster convergence, and interpretation. DTSO functions as a metaheuristic technique responsible for optimizing the parameters of the DNN, improving weight initialization, and increasing convergence rates by effectively searching the solution space without getting stuck at local minima. DNN represents the learning mechanism, which captures high-level features from preprocessed sensory information and contextual data, modeling complicated nonlinear relationships for effective prediction.

DNN for Hybrid Neuro-Symbolic Learning Models: DNN stands for sequential processing of the data, and in this case, the Hybrid DTSO-DNN-based Neuro-Symbolic model is replaced with a classical model using only DNNs. In contrast to other models of layered neural networks, where DNN uses symbolic reasoning based on the knowledge graph and the rules of logic, in the latter, DNN uses solely hierarchical representation based on the input data. In addition, dynamic transient search can be used to optimize the learning, whereas the nonlinear variations of the time-dependent input data are captured in each level of the network.

$$\tilde{w}_{m,j}^s = \sum_{i=1}^{l_{m-1}} X_{j,i}^m z_{m-1,i}^s + a_{m,j} \tag{9}$$

In Equation (9), S is the sample index, and it indicates which input example from the dataset you are computing the neuron's output for. m is the layer index in the neural network, and j is the neuron index within layer m . $\tilde{w}_{m,j}^s$ is the pre-activation value of the j -th unit in the m -th layer for the s -th sample. $z_{m-1,i}^s$ the output of the i -th neuron in layer $m - 1$ for sample s . $\sum_{i=1}^{l_{m-1}}$ is the summation over all inputs to the neuron from the previous layer, and $X_{j,i}^m$ is the weight connecting the i -th neuron in layer $m - 1$ to the j -th neuron in layer m . l is the neuron index in the previous layer $m - 1$. $a_{m,j}$ The bias term for neuron j in layer m .

$$w_{m,j}^s = e(\tilde{w}_{m,j}^s) \tag{10}$$

In Equation (10), the activated output of neuron j in layer m for sample s . This is the value after applying the activation function to the pre-activation $\tilde{w}_{m,j}^s$, and e , where e is the activation function.

DTSO for Data-Driven Approaches: DTSO refers to the data-based optimization technique that is employed within the context of the Hybrid Neuro-Symbolic Learning Model. The major aim of using the technique is to enhance efficiency and learning, in addition to increasing the predictive accuracy of the model. The technique facilitates the efficient processing of uncertain and non-linear data sets obtained as a result of preprocessing sensory inputs.

$$w^{l+1} - w^{l+} = \sum_{j=1}^m \lambda_j \cdot c_j \tag{11}$$

In Equation (11), w represents the weight vector(s) of the neural network or learning model. w^{l+1} is the updated weights at iteration $l + 1$. w^{l+} The current or intermediate weights at iteration l . $\sum_{j=1}^m \lambda_j \cdot c_j$, c_j represents a weighted combination of constraints or corrections applied to the weights. c_j is the j -th constraint vector or correction term. λ_j is a weight or Lagrange multiplier controlling the influence of c_j .

$$c_j = \frac{r_j}{\|r_j\|}, j = 1, 2, \dots, m \tag{12}$$

In Equation (12), the norm (length) of the vector r_j , typically the Euclidean norm, is used to normalize r_j so that c_j is a unit vector, pointing in the same direction as r_j but with magnitude 1. r_j is the raw constraint vector, divide by $\|r_j\| \rightarrow$ unit vector c_j (direction only). In the update formula, scale c_j by $\lambda_j \cdot$ control magnitude, Sum over $j = 1..m \rightarrow$ combine all constraint directions into a single weight update. The process involved in Algorithm 1 outlines a neuro-symbolic approach whereby the DTSO-DNN framework is applied for precise prediction.

Algorithm 1: DTSO-DNN for Hybrid Neuro-Symbolic Learning

```

# INPUT
1 D = load_dataset()
# PREPROCESSING (Z - score)
2  $\mu, \sigma = \text{mean}(D), \text{std}(D)$ 
3  $Z = (D - \mu) / \sigma$ 
# FEATURE EXTRACTION (DWT)
4 W = DWT(Z)
# INITIALIZATION
5  $\theta = \text{initialize\_DNN\_parameters}()$ 
6  $\theta\_best, E\_best = \theta, \infty$ 
# DTSO OPTIMIZATION
7 for t in range(max_iter):
8    $c\_j = r\_j / ||r\_j||$ 
9    $\theta\_new = \theta + \Sigma(\lambda\_j * c\_j)$ 
10   $y\_pred = \text{DNN}(W, \theta\_new)$ 
11   $E\_new = (1/N) * \Sigma(y\_true - y\_pred)^2$ 
12  if  $E\_new < E\_best$ :
13     $\theta\_best, E\_best = \theta\_new, E\_new$ 
14   $\theta = \theta\_best$ 
# FINAL TRAINING
15 model = train_DNN(W,  $\theta\_best$ )
# PREDICTION + SYMBOLIC VALIDATION
16 for x in D:
17  w = DWT(x)
18   $y\_hat = \text{model.predict}(w)$ 
19  label = "Normal" if  $(y\_hat \geq \tau \text{ and } \text{symbolic\_validation}(y\_hat))$  else "Anomaly"

# OUTPUT
20 return labels

```

Shapley Additive Explanations (SHAP)

SHAP calculates how much each feature contributes to the prediction made by the model. For dynamic data-rich scenarios, SHAP can be used for hybrid neuro-symbolic AI to provide explanations for why the system state is classified as either normal, warning, or critical. The use of SHAP in such scenarios is directly related to the research objective of building a reliable, understandable, and intelligent decision system.

Result and Discussion

The performance evaluation of the proposed model (DTSO-DNN), which demonstrates high performance metrics and their explanation shown in Table 2, outperforms baseline models and highlights areas for further optimization and enhancement. The model is implemented in Python and executed on a Windows system with an Intel® Core™ i7-10875H 2.30 GHz processor, leveraging libraries for neural networks, symbolic reasoning, and microgrid simulation.

Table 2: Metrics explanation

Metric	Explanation
Total Harmonic Distortion (THD)	Measures waveform distortion caused by harmonics; lower values indicate higher power quality and reduced electrical stress.
Line Outage Recovery Time	Represents the time required to restore power after a line fault; lower values indicate faster system recovery.
DER Failure Recovery Time	Indicates the time taken to restore distributed energy resources after failure; lower values reflect efficient fault response.
Load Shedding	Measures the amount of load intentionally reduced to balance supply and demand; lower values indicate better system efficiency.
Renewable Energy Utilization	Represents the percentage of renewable energy effectively used; higher values indicate improved sustainability.
Renewable Curtailment	Indicates the percentage of renewable energy not utilized; lower values reflect efficient energy usage.

SHAP for model interpretability and feature importance analysis: Figure 3 indicates how each feature helps predict anomalies through machine learning using SHAP value analysis. It emphasizes the impact that some of the important features, like rule_gas_alert, sensor_pressure, and anomaly_score, have on the prediction made by the model. In the graph, you can see how various feature values, from lowest to highest, affect the predictions made by the model.



Figure 3: Impact of Features on Machine Anomaly Prediction Using SHAP.

Performance evaluation using existing dataset: The comparison carried out in Table 3 and Figure 4 above utilizes the same database of the modified IEEE 33-bus distribution system under different operating conditions, such as normal operation, high penetration of renewables, contingencies, islanding operation, and power quality using NSAI [16]. In such cases where there is high uncertainty, NSAI experiences difficulty sustaining high performance for the IEEE 33-bus distribution network under several conditions. The DTSO-DNN model, is trained on an existing dataset to provide a level playing ground for the comparison. From the obtained results, it is evident that the new DTSO-DNN method outperforms the NSAI technique with regard to all performance measures. By use of deep learning in an attempt to increase resilience to uncertainties, minimize losses, and enhance decision making, the proposed DTSO-DNN model rises above these challenges.

Table 3: Comparison of NSAI Algorithm vs DTSO-DNN method on existing dataset

Performance Metric	NSAI [16]	DTSO-DNN [Proposed]
Total Harmonic Distortion (THD)	43.2%	40.5%
Line Outage Recovery Time	3.5 min	2.8 min
DER Failure Recovery Time	2.8 min	2.0 min
Load Shedding	45.3 kWh	40.5 kWh
Renewable Energy Utilization	93.7% utilization	95.8%
Renewable Curtailment	6.3%	5.5%
Computation Time	0.42 s / 5-min interval	0.36 s / 5-min interval

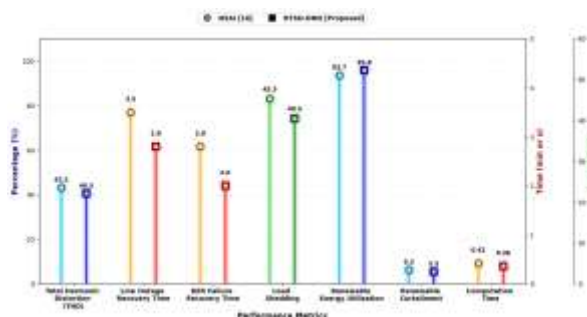


Figure 4: Comparative Performance Analysis of Proposed DTSO-DNN in the existing dataset

Performance evaluation using the proposed dataset: The comparison shown in Table 4 and Figure 5 considers a Neuro-Symbolic Decision Dataset comprising 7000 records, which combines the sensor data, context information, and rules for symbolically making decisions in an explainable manner. To provide consistency between the two models, the proposed DTSO-DNN model and NSAI [16] are trained using the proposed dataset. It is found that the proposed DTSO-DNN model outperforms the benchmark NSAI model by providing lower THD (38.4%), Line Outage recovery time (2.0 min for line outages and 1.8 min for DER failures), less load shedding (39.3 kWh), better renewable energy utilization (97.9%), less curtailment (4.5%), and computation time (0.30 s).

Table 4: Comparison of NSAI Algorithm vs DTSO-DNN method on the Proposed dataset

Performance Metric	NSAI	DTSO-DNN [Proposed]
Total Harmonic Distortion (THD)	42.8%	38.4%
Line Outage Recovery Time	3.0 min	2.0 min
DER Failure Recovery Time	2.5 min	1.8 min
Load Shedding	43.3 kWh	39.3 kWh
Renewable Energy Utilization	95.8%	97.9%
Renewable Curtailment	5.2%	4.5%
Computation Time	0.38 s / 5-min interval	0.30 s / 5-min interval

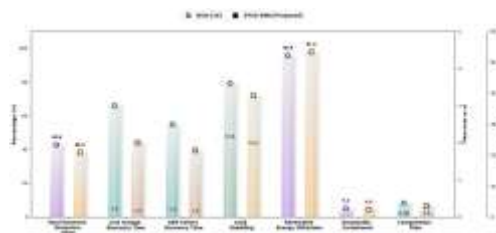


Figure 5: Graphical representation of the Proposed DTSO-DNN Model for the Proposed dataset

Conclusion

The suggested hybrid approach to neuro-symbolic DTSO-DNN and SHAP is very efficient for combining symbolic reasoning and neural networks to guarantee accurate, reliable, and easily interpretable results. The effectiveness of the presented technique is shown through several improvements, such as a decrease in THD (of 38.4%), quicker outage recovery and DER restoration (in 2.0 and 1.8 minutes, respectively), minimized load shedding (of 39.3 kWh), and a rise in the use of renewable energy (97.9%). For AI-based systems in critical applications and energy management, it provides a modern method to perform scalable and explainable calculations. There are limits in the experiment that can prove the efficiency of the model suggested above, with consideration of hardware, high dynamics of energy management systems, and communication delays between nodes. Future research includes the implementation of the approach in real-life situations with a large-scale network and renewable energy sources, and further development of online learning techniques. Hybrid neuro-symbolic energy management can also be positively influenced by increased computation capability, probability inferencing abilities, and interpretation possibilities.

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