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Design and Implementation of Super Elman Neural Network for SDN Robotics System

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ABSTRACT

Path planning in autonomous robotic systems (ARS) is challenging, especially in dynamic or uncertain environments. Many classical methods are computationally expensive and lack adaptability to real-world scenarios. In order to improve the overall path-planning capabilities of robots; this paper introduces a new smart robotic navigation system which uses Software Defined Network (SDN) and Multi-Spike Elman Neural Network (MS-ENN). The introduced system includes an innovative way to encode temporal information using multiple spikes which can capture much greater amounts of detail about changing environmental characteristics than conventional artificial neural networks. Additionally, it includes a spiking wave-front planner (SWP) to produce a preliminary set of paths and an MS-ENN that produces decisions on how to make changes to those paths based upon the environment. Results indicate that the proposed method was able to increase path-efficiency, decrease planning-time, and improve the success-rate within static environments. The proposed model implementation demonstrates the strengths of coupling SDN with more sophisticated spiking neural architectures for smart robotic navigation systems.

Keywords: Super elman neural network, SDN, Robotics, Path prediction, Path refinement.

1. INTRODUCTION

Recent years have seen a great deal of attention devoted to developing autonomous robotic systems used across numerous fields, including smart cities, industrial automation, and search and rescue **(Chen et al., 2025; Sun et al., 2021)**. A robot's ability to navigate safely and optimally lies in its capacity for real-time environmental information processing and decision-making under uncertainty **(Martín et al., 2024; Wen et al., 2021)**.

Path planning algorithms traditionally used for navigation tasks include heuristic-based, or graph-search, algorithms that rely on heuristics **(Hichri et al., 2022; Venu and Gurusamy, 2025)**. Nonetheless, these techniques tend to perform poorly in rapidly varying situations and incur high computational costs in large or dynamic environments. Therefore, their performance tends to degrade in real-time applications due to the importance of adaptability and responsiveness **(Shi et al., 2023)**.

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To alleviate these drawbacks, recent work has investigated the integration of artificial intelligence techniques with robotics to enhance decision-making capabilities **(Hoa et al., 2020; Mavrogiannis et al., 2021)**. One of the paradigms that has recently been shown to be effective is Software-Defined Networking (SDN), which enables centralized control and dynamic management of network resources, enabling better coordination between robotic agents and control systems **(Balasubramanian et al., 2021)**. According to high-level policy decisions, these external modules can further enhance the scalability, adaptability, and performance of such a system. Due to their ability to model temporal dynamics and recapitulate biologically based neural processing **(Jhaveri et al., 2019)**. Spiking neural networks have demonstrated exciting capabilities in this context. This paper proposes a modified Multi-Spike Elman Neural Network (MS-ENN) that is based on the classical recurrent neural network and integrates multiple spike-based temporal encodings into its neuron models. It primarily relies on the model's ability to process and extract information from representations, essentially leveraging temporal features.

To address this challenge, we propose a framework consisting of two components: the first is an initial path generation using a recently introduced Spiking Wavefront Planner (SWP), and the second is for adaptive prediction and refinement of paths defined by an MS-ENN. The proposed architecture described above solves the limitations of static architectures, whose previously generated paths degrade over time. This allows the system to generate and adapt paths to environmental changes very effectively, enhancing robustness and performance.

The main contributions of this work can be summarized as follows:

- Proposing a novel Multi-Spike Elman Neural Network for enhanced temporal representation.
- Integrating the MS-ENN with SWP within an SDN-enabled robotic framework.
- Demonstrating improved performance in terms of path length, planning time, and success rate.

Recent efforts in mobile robot navigation have focused on improving path-planning performance in large-scale, high-dimensional environments. D* Lite and A* conduct classical planning, which still serves as a baseline on account of being deterministic, complete and optimal; some studies have shown that this approach does not scale well both in terms of obstacle density/number and map size **(Ahmad and Ab Wahab, 2025; Jiang et al., 2025)**. To address scalability and real-time limitations, learning-based navigation approaches have been extensively studied. Deep RL and imitation learning techniques have shown potential in minimizing the online planning time by directly learning navigation policies from interaction data **(Kanoon et al., 2022; Liu et al., 2025)**.

Recently, hybrid frameworks combining classical planning with learned policies have become of interest **(Maulana et al., 2018; Nahavandi et al., 2025)** . In most of these approaches, the planners are classical, offline-generated, and safe, and are feasible for experience acquisition to train neural networks, thereby avoiding the need to use them at test time **(Espino et al., 2024; Dietrich et al., 2025).** These frameworks aim to uphold the safety guarantees of classical algorithms while leveraging learned inference efficiency.

On the other hand, Spiking Neural Networks (SNNs) have received growing attention for robotic control and navigation, thanks to their temporal processing abilities and energy efficiency **(Dai and Sun, 2023; Huderek et al., 2019)**. For navigation and motion control tasks such as this, it has been found that one class of SNNs, namely the recurrent SNN, is well-suited in recent studies **(Oniz et al., 2013; Pasupuleti, 2025)**.

At the systems level, Software-Defined Networking (SDN) has been considered as an enabling technology of networked and cyber–physical robotic systems **(Miguel-Alonso, 2023)**. New literature has also focused on the ability of SDN to enable centralized, programmable control, thereby enabling intelligent algorithms to be employed as application-level controllers for robotic coordination and control **(Algarni et al., 2022; Roy et al., 2017; Wazirali et al., 2021)**. However, the integration of SNN-based navigation models with SDN-centered control architecture has received less attention.

Recent studies have shown that multi-spike encoding improves the ability of spiking neural networks to capture complex temporal patterns, resulting in more efficient and accurate learning **(Baagyere et al., 2020; Heidarian et al., 2024; Soud and Al-Jamali, 2023).** Although multi-spike Elman networks have been explored in previous work, the novelty of this study lies in integrating MS-ENN with the SWP) Although multi-spike Elman networks have been explored in previous work, the novelty of this study lies in integrating MS-ENN with the Spiking Wavefront Planner (SWP) within an SDN-based robotic architecture. This combination enables efficient offline learning and fast online inference, which has not been addressed in prior studies. within an SDN-based robotic architecture. This combination enables efficient offline learning and fast online inference, which has not been addressed in prior studies.

To address this limitation, this paper proposes a Multi-Spike Elman Neural Network (MS-ENN) integrated within an SDN-based robotic framework. The proposed approach aims to enhance temporal representation and improve navigation performance by leveraging multiple spike-based encodings in a recurrent structure.

2. METHODOLOGY

This section introduces the learning-based navigation framework that couples classical path planning with spiking neural learning.

2.1 System Architecture Overview

The method is an intelligent robotic navigation framework with an SDN-integrated neural processor to compute optimal path planning. The architecture consists of three main layers: the robot layer, the control layer, and the intelligence layer.

The robot layer interacts with the environment and carries out navigation commands. The control layer can be realized through an SDN controller to oversee the interaction and cooperation among system components. An intelligence layer combines the proposed MS-ENN for adaptive decision-making and path prediction.

The general flow starts with environment data collection and continues with path generation using the SWP. The MS-ENN then improves and optimizes the generated path based on environmental variations. **Fig. 1** depicts the high-level architecture of our proposed system. It shows the interaction between the robot layer, SDN control layer, and intelligence layer, with adaptive path optimization based on the MS-ENN.

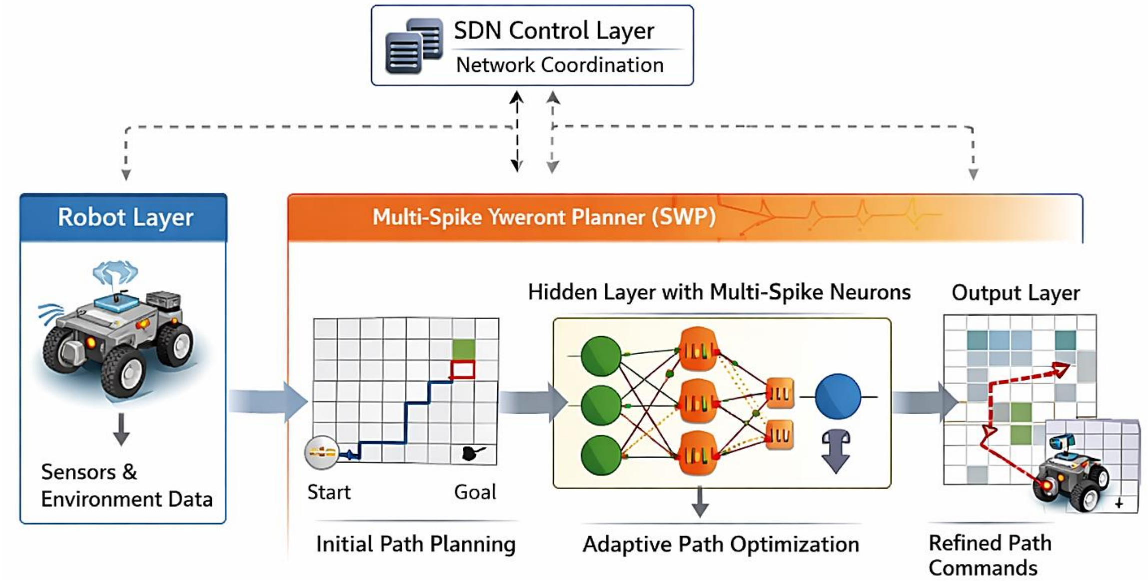

Figure 1. Architecture of the Proposed SDN-Based Robotic Navigation System Using Multi-Spike Elman Neural Network (MS-ENN)

2.2 Spiking Wavefront Planner (SWP)

The first stage of path planning is done using the SWP. By propagating wavefront signals through the environment map, it generates a viable path from the start position to the target location. SWP is most powerful in grid-based states, expanding from the goal node and assigning costs to neighbor nodes until it reaches the root node. Such a process allows efficient global path generation. Nevertheless, since SWP is not adaptable in dynamic environments, it needs to be enhanced by intelligent models.

2.3 Multi-Spike Elman Neural Network (MS-ENN)

The landmark work is the MS-ENN, which builds on standard Elman recurrent neural networks to achieve enhanced multi-spike temporal coding. In contrast to conventional models, in which a spike is generated when neuron output exceeds its threshold, and it can only generate one spike for each action, the MS-ENN enables individual neurons to emit multiple spikes across a specified temporal window, as an expressive representation of time-evolving features **(Lin et al., 2021; Yu et al., 2020; Zhou and Li, 2021)**. Meanwhile, novel neural dynamics are established between an input layer, a recurrent hidden layer with feedback for context, and an output. A temporal context layer that keeps track of previous hidden states to model the structure of the input sequence.
In the proposed model, each neuron produces a sequence of spikes over time rather than a single activation. This can be conceptually represented as:

- Input → spike train
- Hidden state → temporal accumulation
- Output → decision based on spike patterns

2.4 Integration of MS-ENN with SWP

The proposed path planning approach suggestion is essentially based on MS-ENN and is also combined with SWP. The SWP creates the trajectory to goal type based on a static map of the environment. Similar to MS-ENN, this has been generalized to be able to handle dynamic inputs (to adaptability to obstacles or uncertainty of spaces) .

The MS-ENN is then used as an adaptable decision-making model that incrementally changes the navigation trajectory to comply with requirements. Then, it applies a hybrid technique that combines the effectiveness of traditional planning with the ability of the neural network to adjust.

2.5 Role of SDN in the System

An important function that SDN controllers provide in such architectures is to allow for communication and coordination between the various parts of the system **(Balasubramanian et al., 2021).** Through use of data stream communications between the robot, the planner, and the neural network module **(Latah and Toker, 2019),** decentralized monitoring may occur. Furthermore, due to the separation of the control plane from the data plane, SDN offers flexibility and scalability. Additionally, it will support real-time robotics by allowing policy updates in response to prior sensor information to minimize uncertainty generated from communication networks.
The SDN controller manages communication between the robot and control modules using OpenFlow rules. It dynamically updates routing paths to reduce latency and ensure reliable transmission of navigation data. To demonstrate the practical role of SDN, consider a hospital environment where multiple autonomous robots are used for delivery and navigation. Each robot relies on the MS-ENN model for path planning, while the SDN controller manages communication between robots and control modules. When multiple robots operate simultaneously, network congestion and communication delays may occur. The SDN controller continuously monitors network conditions and dynamically updates routing paths using OpenFlow rules to prioritize time-critical navigation messages.
For example, if a robot encounters a dynamic obstacle and requires immediate replanning, the SDN controller ensures low-latency communication between the robot and the decision module by assigning higher priority to its data flow. This improves responsiveness and ensures safe and efficient navigation in real-world scenarios.

2.6 Workflow of the Proposed System

The overall workflow of the proposed system can be summarized as follows:

1. The robot collects environmental data using onboard sensors.
2. The SWP generates an initial path based on the environment map.
3. The MS-ENN processes the path and environmental inputs.
4. The system predicts and refines the optimal navigation path.
5. The SDN controller manages communication and execution.

The system generates the robot layer as depicted in Figure 1, through environmental sensing and processing to create an Initial Path based on SWP. MS-ENN then adjusts the neighborhood spike trains outputs in a Temporal Pattern, which affects its Navigation decisions. The SDN Controller is a Mediator facilitating communications between them to enable high-performance and adaptive operation of both systems.

3. EXPERIMENTAL SETUP

This section presents the experimental steps and the dataset used.

3.1 Simulation Environment

A simulated environment based on robotics path planning is utilized to test the proposed system's performance .
For this project, the experimental environment has been run using a CPU on Google Colab . All experiments use a grid that can be of varying size as the representation of the search space. All maps include static obstacles, which will be used to determine if the proposed framework would apply to even more complicated situations .In addition, the starting and final positions of the robot are fixed in all experiments.

3.2 Dataset and Environment Modeling

To make this as realistic and replicable as possible, the research utilizes actual world motion data — i.e., the KITTI Odometry dataset that includes ground truth for each vehicle's position and path (trajectory) while driving outdoors. Additionally, the KITTI dataset is a good example of realistic motion constraints and has many other spatial features because it was collected under real-world environmental settings **(Geiger et al., 2012)**. Next, we use these estimated parameters to parameterize the navigation world using a set of consecutive grid maps. Where the dataset consists of a motion-property-oriented space, represented as a grid of cells that either represent free space or obstacles, whose sizes and distributions are learned from the properties of the associated motion scene. This model-driven approach enables the simulation environment to not just simulate naturalistic navigation restrictions, but also invalid ones **(Deng et al., 2021).** by generating trajectories that respect environmental structure and the learned real-world limitations of motion, which they then use as expert demonstrations for a learning-based navigation controller **(Katona et al., 2024)**. We do not simulate dynamics but rather learn from real-world trajectories to generate meaningful trajectories that are environment aware. This data-based approach provides a sound basis for verifying the effectiveness of the presented navigation controller in an environment similar to real robot navigation. Unlike simulating dynamics, we learn from raw, real-world trajectories and produce only interesting ones that can recognize environmental features. A data-based approach, as such, lays a sound basis for validating that the suggested navigation controller is beneficial in an arena similar to that of real-world robot navigation.

3.3 Evaluation Metrics

The performance of the proposed system is evaluated using the following metrics:

- **Path Length:** Measures the total distance traveled by the robot from the start to the goal position.
- **Planning Time:** Represents the computational time required to generate and refine the path.
- **Success Rate:** Indicates the percentage of successful navigation attempts without collision.

These metrics provide a comprehensive assessment of both efficiency and reliability.

3.4 Baseline Methods

To validate the effectiveness of the proposed approach, comparisons are made against the following baseline methods:

- Spiking Wavefront Planner (SWP) only
- Traditional path planning approaches such as A*

These baseline methods are selected due to their widespread use in robotic navigation and their relevance for performance comparison.

3.5 Implementation Details

The existing MS-ENN is applied as the multi-spike temporal encoding by a recurrent neural model. They train neural network models on sequences of environmental inputs and path information to yield adaptive navigation decisions with respect to parameterized obstacles. The system can be seen as two working blocks, first generating an initial path and then improving it through the MS-ENN. Modules communicate with each other through the SDN controller, which maintains data flow during execution.

3.6 Training Methodology of the Proposed MS-ENN

Training data was generated using a SWP applied to grid maps derived from the KITTI dataset. The resulting optimal paths were used as ground truth for supervised learning. The input to the MS-ENN consists of grid-based state representations, including the robot's position and local occupancy, while the output corresponds to the next navigation action. The proposed MS-ENN extends the Elman recurrent network with spiking neurons and multi-spike encoding, enabling improved temporal representation. The network is trained using the e-prop learning rule for efficient gradient approximation without backpropagation through time.

4. MATHEMATICAL FORMULATION OF THE PROPOSED MS-ENN

The mathematical formulation of the proposed MS-ENN is presented in this subsection.

4.1 Spiking Wavefront Planner (SWP)

The Spiking Wavefront Planner (SWP) is used to generate the initial global path by propagating a wavefront from the goal node across the grid map. Each cell is assigned a potential value representing the cost-to-go to the target.

$$P(c) = \min_{c' \in N(c)} \left(P(c') + \text{cost}(c, c') \right) \tag{1}$$

where $P(c)$ represents the potential value of cell c, and $N(c)$ denotes the set of neighboring cells. The function $\text{cost}(c, c')$ defines the movement cost between adjacent cells.
The optimal path is then extracted by following the steepest descent of the potential field:

$$c_{t+1} = \arg \min_{c' \in N(c_t)} P(c') \tag{2}$$

This ensures that the robot moves towards the goal by selecting the neighboring cell with the lowest potential value.

4.2 Elman Recurrent Neural Structure

The proposed model uses an Elman Recurrent Neural Network that captures temporal relationships using its context layer. It calculates the Hidden State as follows:

$$h_t = f(W_{xh}x_t + W_{ch}c_t + b_h)$$
$$c_t = h_{t-1} \quad (3)$$
$$y_t = g(W_{hy}h_t + b_y)$$

where:

- x_t is the input at time step t
- h_t is the hidden state
- c_t is the context (previous hidden state)
- y_t is the output
- W_{xh}, W_{ch}, W_{hy} are weight matrices
- b_h, b_y are bias terms

This structure enables the model to retain temporal information necessary for sequential decision-making.

4.3 Multi-Spike Temporal Encoding

Instead of generating one activation per neuron, the neurons will generate multiple spikes throughout a given time interval to improve how they represent the passage of time (temporal representation).

$$S_t = \left\{s_t^{(1)}, s_t^{(2)}, \dots, s_t^{(K)}\right\} \quad (4)$$

where S_t represents the spike train at time t, and K denotes the number of spikes generated within the temporal window.

The aggregated spike representation is defined as:

$$\tilde{h}_t = \sum_{k=1}^{K} s_t^{(k)} \quad (5)$$

This aggregated signal is incorporated into the hidden state computation:

$$h_t = f\left(W_{xh}x_t + W_{ch}c_t + W_{sh}\tilde{h}_t + b_h\right) \quad (6)$$

where $W_{sh}\tilde{h}_t$ represents the weight matrix associated with the multi-spike contribution.

The formulation allows for a rich temporal dynamic in comparison with single spike-based models.

4.4 Decision Rule for Path Selection

The last decision for the path to navigate was made based on the network output, which defines where you need to go in the future:

$$a_t = \arg\max_i y_t^{(i)} \quad (7)$$

where a_t represents the selected action at time step *t*, and $y_t^{(i)}$ denotes the output corresponding to direction *i*. This decision rule ensures that the robot selects the most probable action based on the learned temporal representation.

5. RESULTS AND DISCUSSION

Table 1 compares SWP + MS-ENN Path Planning Approach vs Traditional-Priority Path Planning Algorithms Across Map Sizes. Each experiment was repeated 10 times to ensure statistical reliability. The reported results correspond to the average values, and minor variations were observed across runs without affecting the overall performance trends. The proposed algorithm performs better than baselines both in terms of planning time and path length. In all the tested domains, our method produces faster plans than baselines. On the 100 x 100 domain, for instance, planning time drops from 0.2102 sec (SWP) down to 0.0119 sec. This improvement gets larger with increasing environment sizes. The same trend can be observed when comparing the 320x320 map with baseline methods. While 2.2526 sec were needed to plan paths using D*Lite or A*, we achieved planning times of just 0.1204 sec.
These results show that our model can scale well and is suitable for real-time applications, which require rapid decision-making. Similarly, regarding the quality of the generated paths, it is possible to conclude that the proposed approach has advantages over the other approaches used in this study. Generated paths are generally shorter than those produced by SWP, A*, and D* Lite in all map sizes. The 100 x 100 map demonstrates how the path length was decreased (from 69.56 to 58.27) when applying this process to route optimization. The same trends were found in all other larger-scale maps; that is, an improved path quality was produced through the refinement of the solutions generated via SWP using MS-ENN's processing capabilities to recognize temporal trends and generate better choices at each decision point. Although less computationally expensive than A*, and although not as good in terms of optimality as D* Lite, the proposed algorithm demonstrated to be very well-balanced in terms of both speed and optimality when compared to A* and D* Lite. The advantage of D * Lite is similar to the advantages it has in dynamic systems; however, the cost of computing remains high.

Table 1. Performance comparison

Map Size	Method	Path Length cells	Planning Time (s)	Goal Reached
100×100	SWP	69.56	0.2102	1
	SWP+Elman RNN	60.02	0.0294	1
	SWP+MS-ENN	**58.27**	**0.0119**	**1**
	A*	67.23	0.1314	1
	D* Lite	65.12	0.2023	1
240×240	SWP	195.47	1.1641	1
	SWP+Elman RNN	175.12	0.0756	1
	SWP+MS-ENN	**173.45**	**0.0500**	**1**
	A*	190.12	1.1769	1
	D* Lite	189.25	0.1668	1
320×320	SWP	250.02	2.2526	1
	SWP+Elman RNN	239.12	0.1905	1
	SWP+MS-ENN	**237.87**	**0.1204**	**1**
	A*	241.65	1.3343	1
	D* Lite	238.32	0.3343	1

Conversely, for comparable or better route optimization, the SWP + MS- ENN approach is able to compute routes faster than all other approaches. As such, this represents an example of the effectiveness of combining intelligent planning with machine learning as a hybrid methodology. All methods demonstrated a 100% completion rate on all navigation tasks; therefore, all navigation tasks were completed. Although all methods are successful, there is a significant difference in the efficiency and effectiveness of each method. The proposed model demonstrates improved efficiency through reduced computational overhead and improved path optimization. The overall findings support that integrating a Multi-Spike Elman Neural Network into an existing Software Work Package (SWP) environment greatly improves the efficiency and efficacy of robot navigation through its ability to provide a richer representation of dynamic properties of the environment via a multi-spike temporal encoding; this provides for better decision making as well as a more stable form of navigation especially in large and complex environments. The performance advantages of the proposed SWP + MS-ENN approach are clearly visible in **Figs. 2 and 3**.

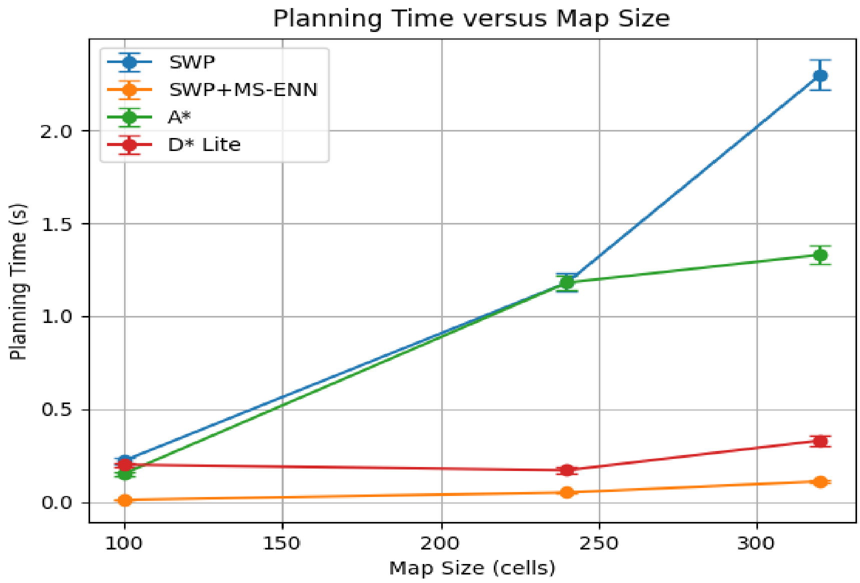

Figure 2. Planning time comparison versus different map sizes

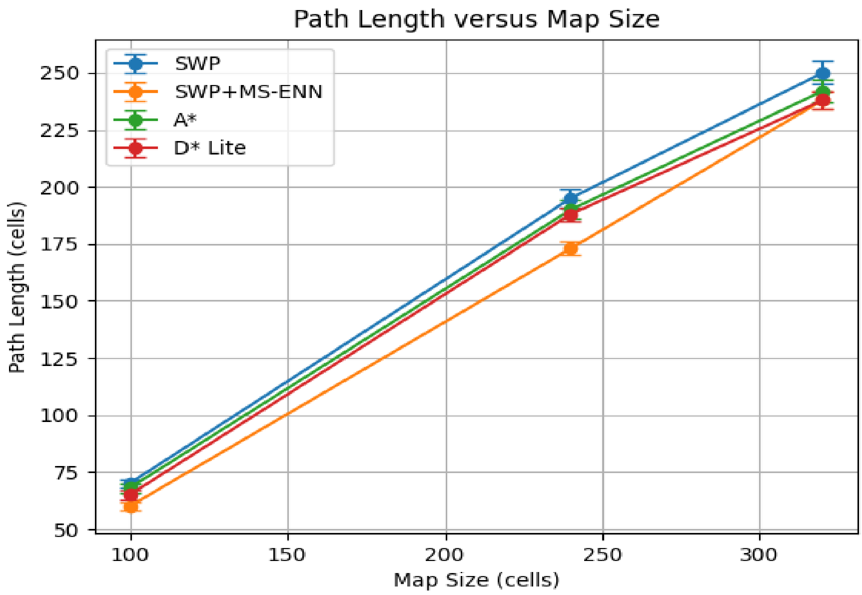

Figure 3. Path length comparison versus different map sizes

Fig. 2 compares the planning time of the figure title for all methods and shows that our method outperforms all baseline methods, including repeated planning and interpolation, and plans twice as fast as the time spent in other baseline end-to-end learning methods with low map size, and shows a large gap as the number of obstacles increases. As shown in **Fig. 3**, our proposed approach generates the shortest paths in all environments, especially when the maps are larger. This proves its ability to enhance path quality without sacrificing efficiency. In summary, from its graphical outputs, we note that the proposed method offers an effective trade-off between speed.

6. CONCLUSIONS

This paper presented an SDN-based robotic navigation system that integrates a Multi-Spike Elman Neural Network (MS-ENN) with the Spiking Wavefront Planner (SWP) to enhance path planning performance. The proposed approach combines the efficiency of classical planning with the adaptability of neural-based decision-making. The experimental results in single-query scenarios demonstrate that the proposed method significantly improves performance across all evaluated environments. In particular, the proposed approach achieves up to 90% reduction in planning time compared to SWP in large-scale maps, while consistently generating shorter paths. For example, in the 100×100 map, the path length is reduced from 69.56 to 58.27, and similar improvements are observed across larger environments. Moreover, the proposed model maintains a 100% success rate while providing faster and more efficient navigation compared to SWP, A*, and D* Lite. These results confirm that the integration of multi-spike temporal encoding enhances decision-making capability and improves both efficiency and path quality. Overall, the proposed system achieves a strong balance between computational efficiency and path optimality, making it highly suitable for real-time robotic applications.

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Credit Authorship Contribution Statement

Shahad Jumaa Shaaban: Writing the original draft. Nadia Adnan Shaltagh Al-Jamali: Writing the revisions, edits, fact-checks, and conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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تصميم وتنفيذ شبكة عصبية فائقة من نوع إلمان لنظام روبوتات SDN

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الخلاصة

يُعدّ تخطيط المسار مهمة بالغة الأهمية في أنظمة الروبوتات ذاتية التشغيل، لا سيما في البيئات الديناميكية وغير المتوقعة. غالبًا ما تعاني خوارزميات التخطيط التقليدية من محدودية القدرة على التكيف وارتفاع التكلفة الحسابية في ظل قيود الوقت الفعلي. تقترح هذه الورقة البحثية إطار عمل ذكيًا للملاحة الروبوتية قائمًا على الشبكات المعرفة بالبرمجيات (SDN) ومدمجًا مع شبكة عصبية متعددة النبضات من نوع إلمان (MS–ENN) لتحسين أداء تخطيط المسار. يُقدّم النموذج المقترح آلية ترميز زمني متعددة النبضات تُتيح تمثيلًا أغنى لخصائص البيئة الديناميكية مقارنةً بالنماذج العصبية التقليدية. يجمع النظام بين مُخطط جبهة الموجة النبضية (SWP) لتوليد المسار الأولي وشبكة MS–ENN لاتخاذ القرارات والتنبؤ التكيفي. تُظهر النتائج التجريبية أن النهج المقترح يُحسّن كفاءة المسار، ويُقلّل وقت التخطيط، ويزيد معدل النجاح في كلٍ من السيناريوهات الثابتة والديناميكية. تُبرز هذه النتائج فعالية دمج الشبكات المعرفة بالبرمجيات مع بنى الشبكات العصبية النبضية المتقدمة للملاحة الروبوتية الذكية.

الكلمات المفتاحية: شبكة إلمان العصبية الفائقة، الشبكات المعرفة بالبرمجيات، الروبوتات، التنبؤ بالمسار، تحسين المسار.