国立陽明交通大學

National Yang Ming Chiao Tung University

LEOPARD: Parallel Optimal Deep Echo State Network Prediction Improves Service Coverage for UAV-assisted Outdoor Hotspots

Haoran Peng, A.-H. Tsai, Li-Chun Wang, *National Chiao Tung University*
Zhu Han, *University of Houston*

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UAV-assisted Outdoor Hotspots

➢ Background

✓ The UAV- BSs have a great potential in providing on-demand communications services for dynamic flash crowds in marathon, outdoor activities and etc.

➢ Problem

✓ User movements pose a significant challenge on fast tracking for avoiding service interruption.

➢ Objective

✓ The UAV-BSs are repositioned dynamically to provide seamless services for flash and random crowds, while minimizing the energy consumption in UAV-BSs' trajectories.

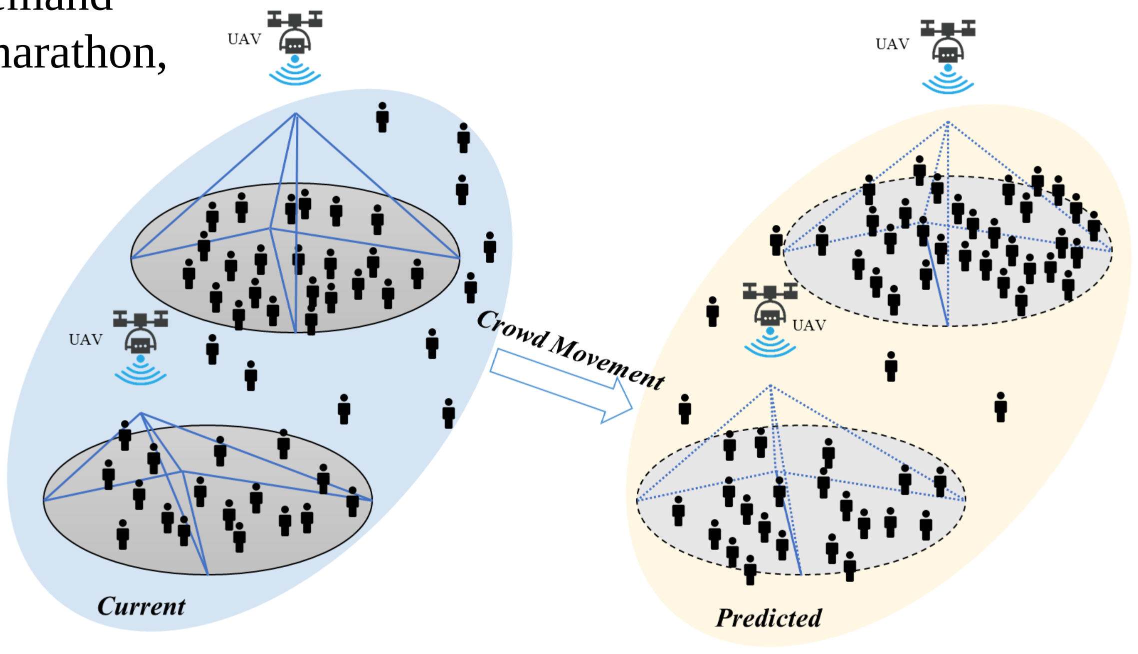


Fig. 2. UAV-aided communications for dynamic scenarios.

Limitations Of The State-of-the-arts

	Contribution	Limitation
Peng, et. al, [1]	The dynamic placement problem of UAV-BSs is studied.	Inaccurate prediction.
Fotouhi, et. al, [2]	Finding the optimal placement of the UAV-BSs while serving the UEs in the target area.	Cannot track the UEs.
Alzenad, et. al, [3]	Maximizing the number of served users with the minimum transmit power.	Static scenarios.
Bayerlein, et al. [4]	Finding the optimal trajectory of an UAV-BS to serve multiple users.	Energy-consuming.

[1] Peng, Haoran, et al. "A predictive On-Demand placement of UAV base stations using echo state network." 2019 IEEE/CIC International Conference on Communications in China (ICCC). IEEE, 2019.
[2] A. Fotouhi, M. Ding, and M. Hassan, “Dynamic base station repositioning to improve performance of drone small cells,” in IEEE Global Communications Conference Workshops (GLOBECOM Wkshps), San Diego, CA, Dec. 2016.
[3] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu, “3-Dplacement of an unmanned aerial vehicle base station (uav-bs) for energyefficient maximal coverage,” IEEE Wireless Communications Letters, vol. 6, no. 4, pp. 434–437, Aug. 2017.
[4] H. Bayerlein, P. De Kerret, and D. Gesbert, “Trajectory optimization for autonomous flying base station via reinforcement learning,” in IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Kalamata, Greece, Jun. 2018.

The Proposed Solution—Consists of Three Steps

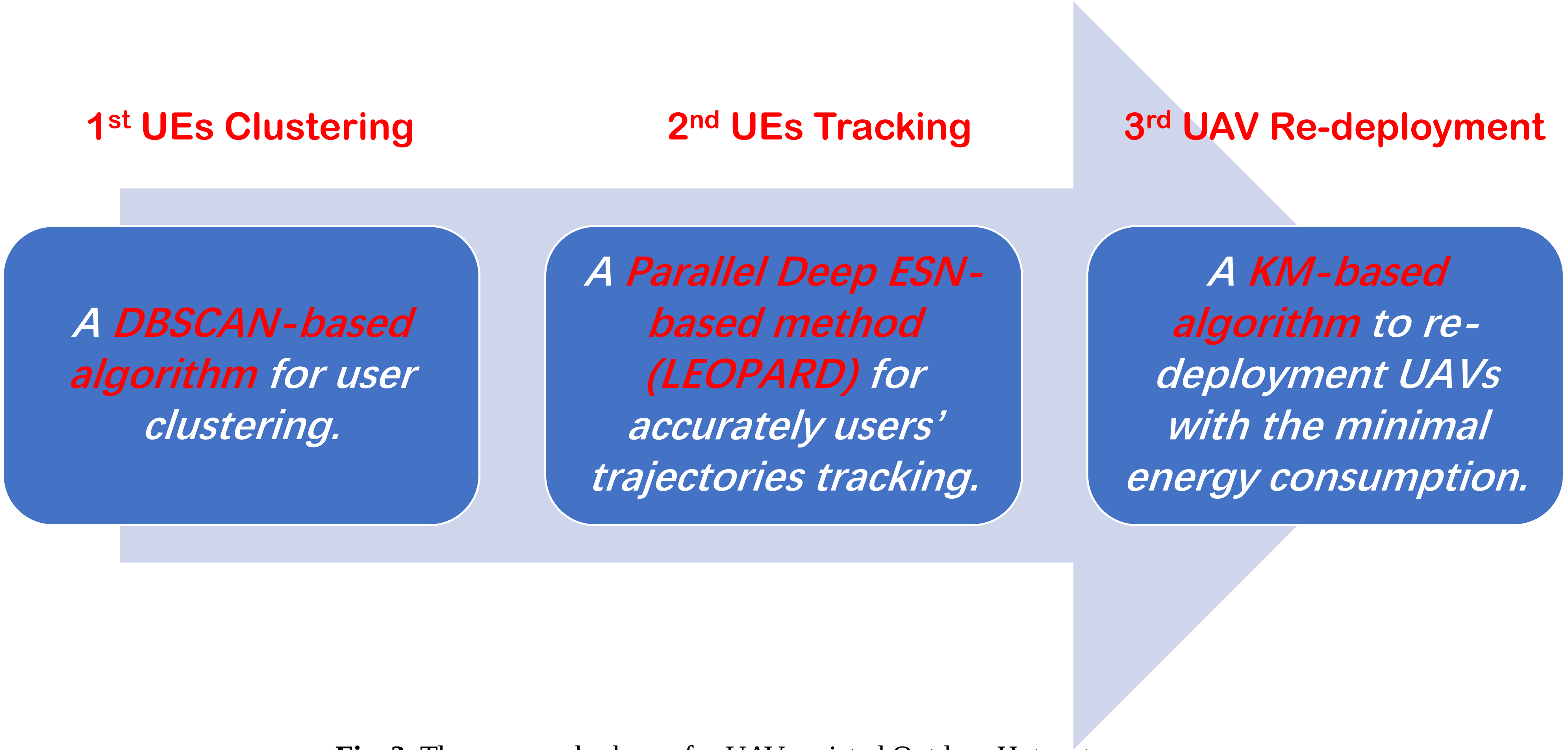


Fig. 3. The proposed scheme for UAV-assisted Outdoor Hotspots.

Why is ESN chosen for Crowd Movement Estimation?

➢ ***Short computation time* and *low energy cost*.**

1) Containing a large number of neurons;

2) The connection between neurons is generated randomly;

3) The links between neurons are sparsity.

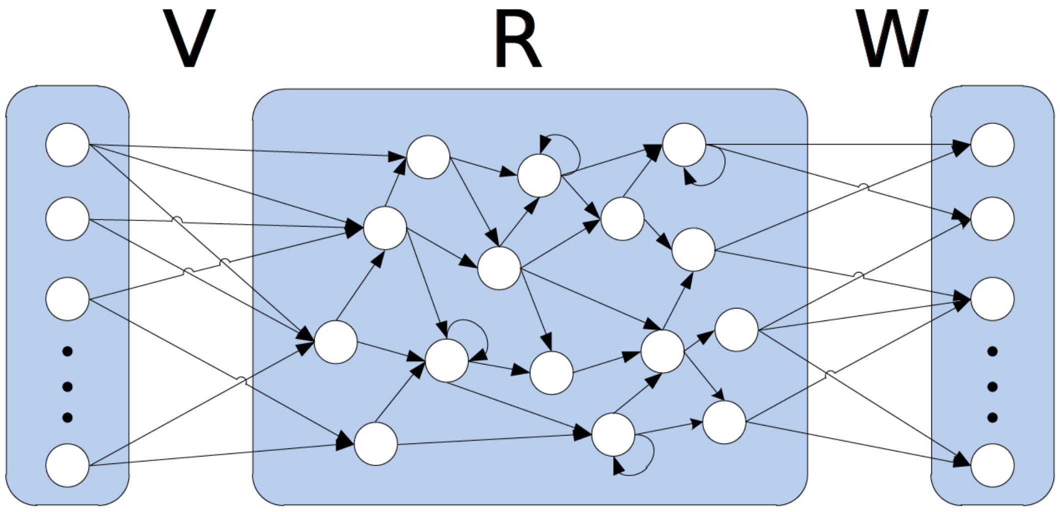


Fig. 7. The framework of an echo state network.

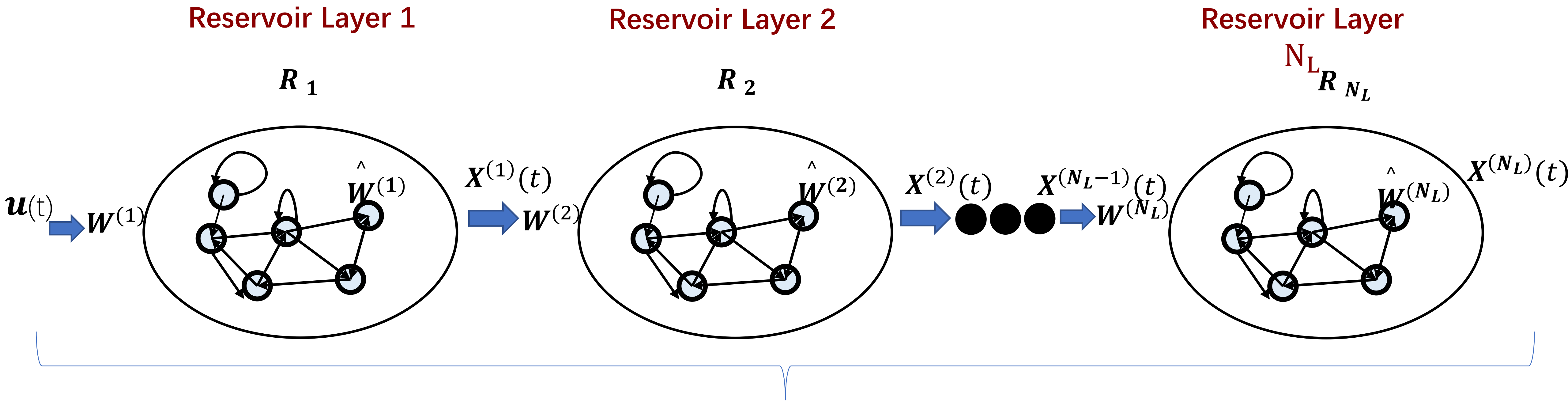
➢ ***V represents the input weight matrix,***

➢ ***R is the reservoir weight matrix***

➢ ***W is the output weight matrix.***

What's The Deep ESN Algorithm

➢ ***Reservoir architecture of the Deep Echo State Network.***



$$X(t) = (X^{(1)}(t), X^{(2)}(t), \dots, X^{(N_L)}(t))$$

Fig. The Reservoir Architecture of A Deep Echo State Network.

[6] Gallicchio, Claudio, and Alessio Micheli. "Deep echo state network (deepesn): A brief survey." *arXiv preprint arXiv:1712.04323* (2017).

The Architecture of LEOPARD

We present a novel paralLEl Optimal deeP echo stAte netwoRk preDiction (LEOPARD) approach, aiming to provide a **fast and accurate prediction** of UE's movement (just like a leopard).

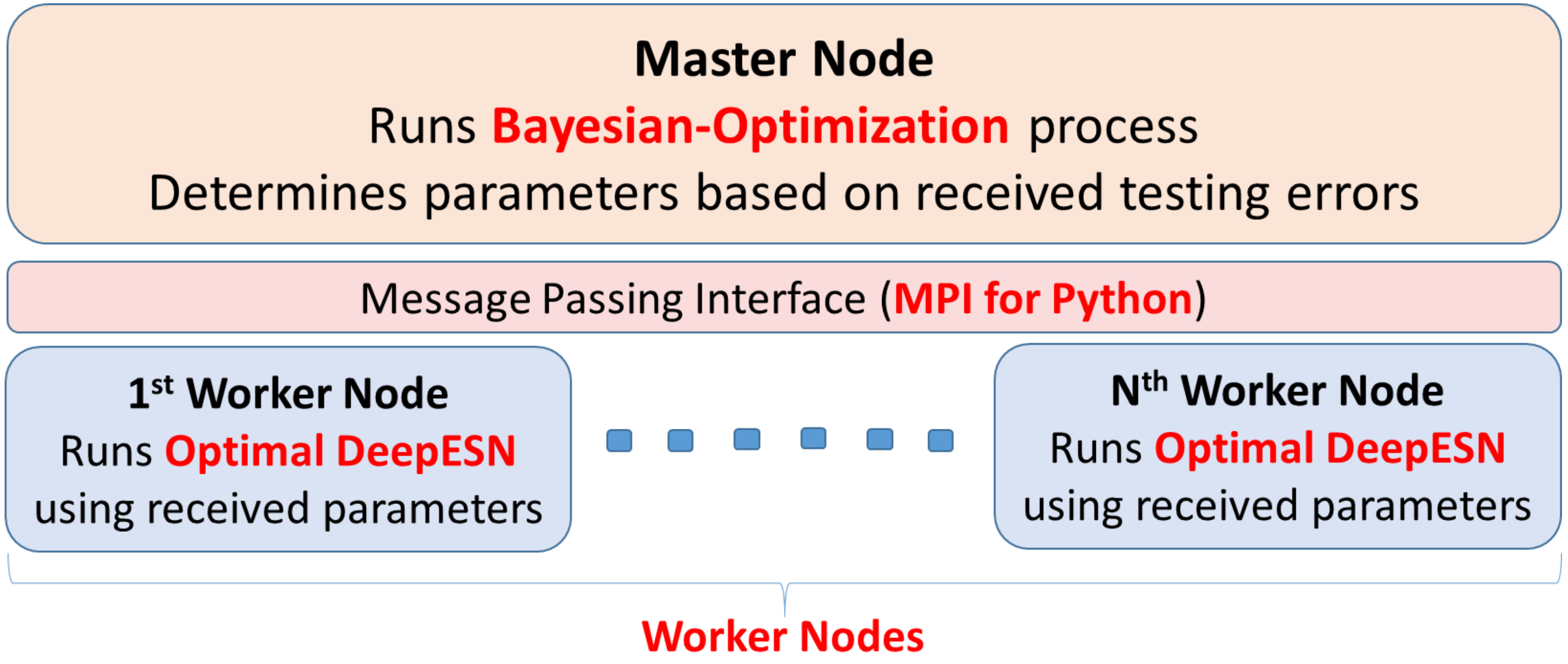


Fig. The proposed LEOPARD for accurately trajectories tracking**.**

Energy-Efficient Re-deployment UAVs

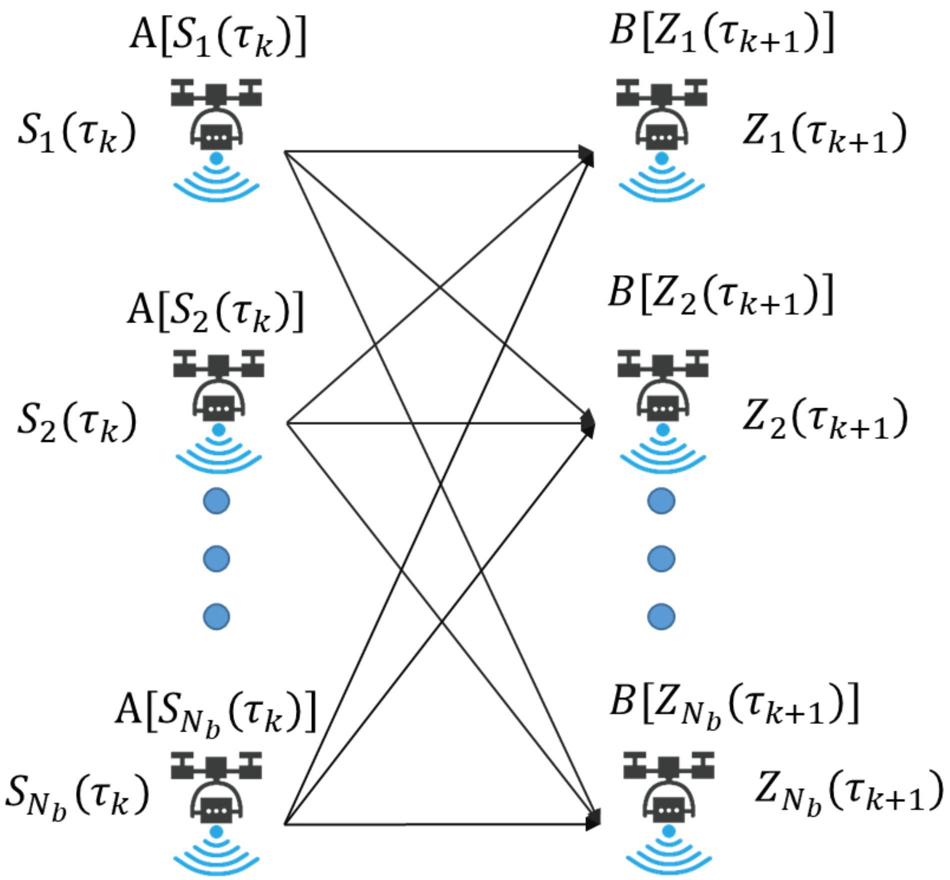


Fig. Re-position matching of multiple UAV-BSs.

- **Without consider the environment factor.**

- *The summation of all UAV-BSs' moving distance is smaller, the energy will be consumed less.*

- *It can be formulated as a well-known problem——Minimum Weighted Bipartite Matching.*

Simulation Results for LEOPARD

- The predicted trajectory by LEOPARD is closest to the actual trajectory among all predictions.

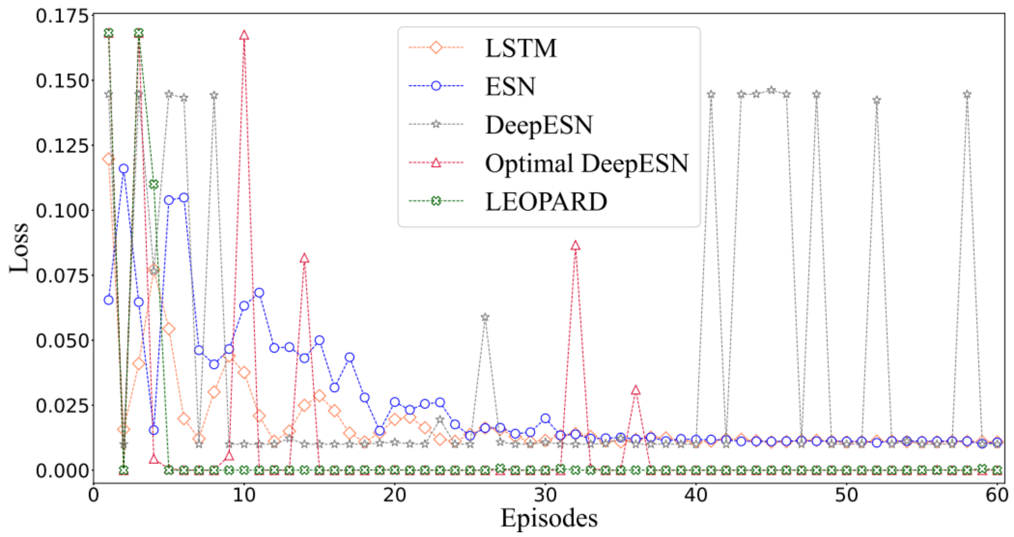


Fig. The convergence behavior of the proposed LEOPARD and benchmarks

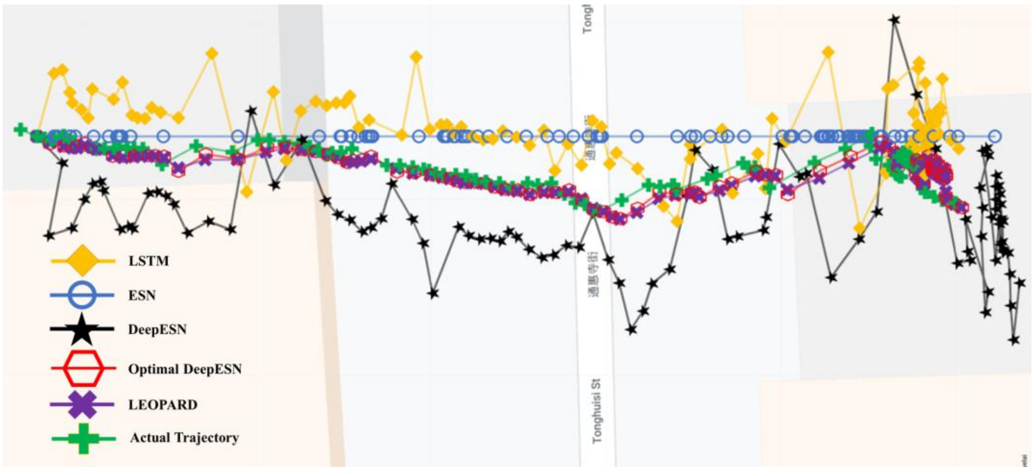


Fig. The actual trajectory vs predicted trajectories.

Simulation Results for LEOPARD

➢ Simulation Results

- ✓ The prediction accuracy of the proposed LEOPARD, combining DeepESN, BOA, and MPI techniques, is **78%** and **67%** better than the state-of-the-art **shallow ESN** and the **original deep ESN**, respectively.

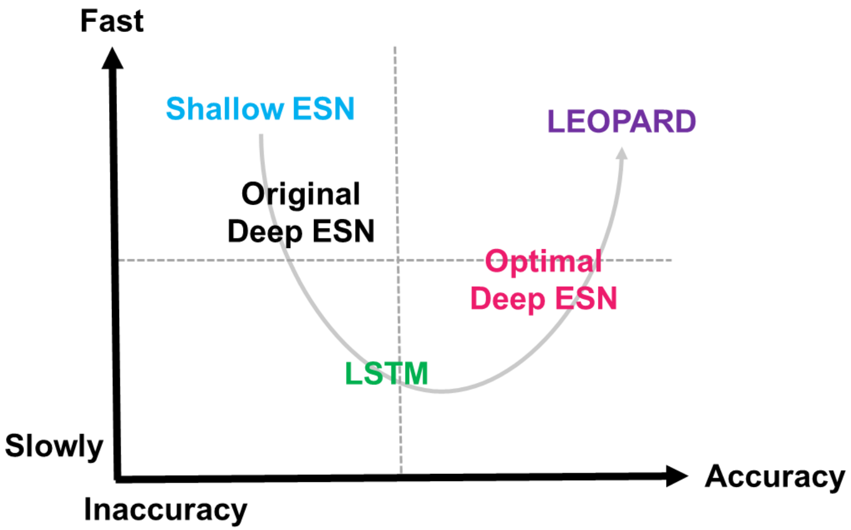


Fig. The comparison between LEOPARD and benchmarks.