Appendix

1. Discussion

This paper proposes an neural architecture search (NAS) framework that can automatically design promising STGNN architectures for target tasks without domain expertise and manual intervention, rather than proposing a specific fixed STGNN design. The purpose of Figure.1 is mainly to show our backbone architecture and the designed search space. The contribution of this work primarily lies in the improvement of existing NAS methods. Our source codes are available at https://github.com/Ypo6opoc/EMTSF.

2. Discussion about the genetic approach in section 3.3

In EMTSF, genetic algorithms are used to heuristically identify the optimal STGNN architecture for the given task. Specifically, we encode each randomly initialized STGNN architecture as chromosomes by encoding strategy, then evaluating their fitness on the target dataset, promising individuals are selected based on fitness, and their chromosomes are subjected to crossover and mutation operations to generate new offspring architectures and form a new population, by iteratively updating the population of candidate architectures, we could identify the optimal STGNN architecture.

3. Discussion about the performance of EMTSF on multistep forecasting

In Table 2, EMTSF excels on Horizon 3 and 6, but some metrics are not optimal on Horizon 12. There are two main reasons for this: (1) EMTSF doesn't incorporate additional domain information, such as road distance, as used in methods like GMAN. (2) When searching for architectures on multi-step forecasting tasks, EMTSF computes the architecture's fitness by averaging the MAE across all 12 prediction horizons, rather than conducting specific searches for only Horizons 3, 6, and 12. In fact, a modification of the fitness calculation can help to improve the performance of EMTSF on specific horizons.