Research experience/interests review

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Outlines

1. **Economical analysis of ride-sourcing market/optimization**
    - **1.1. Dynamic vacant car-passenger meeting model**
    - **1.2. Pricing strategies in ride-sourcing market**
    - **1.3. Solution method: Approximate Dynamic Programming**

2. **Shared mobility's impact on transportation system**
    - **2.1. Didi order data review**
    - **2.2. Shared mobility's influence on the vehicle use and purchase willingness**

3. **Transportation system analysis**
    - **3.1. Deep Learning in on-demand ride service's passenger demand prediction**
    - **3.2. Reinforcement Learning in passenger-vehicle matching problem**
    - **3.3. Machine Learning in short-term traffic speed prediction**

1. Economical analysis of ride-sourcing market

1.1. Dynamic vacant car-passenger meeting model

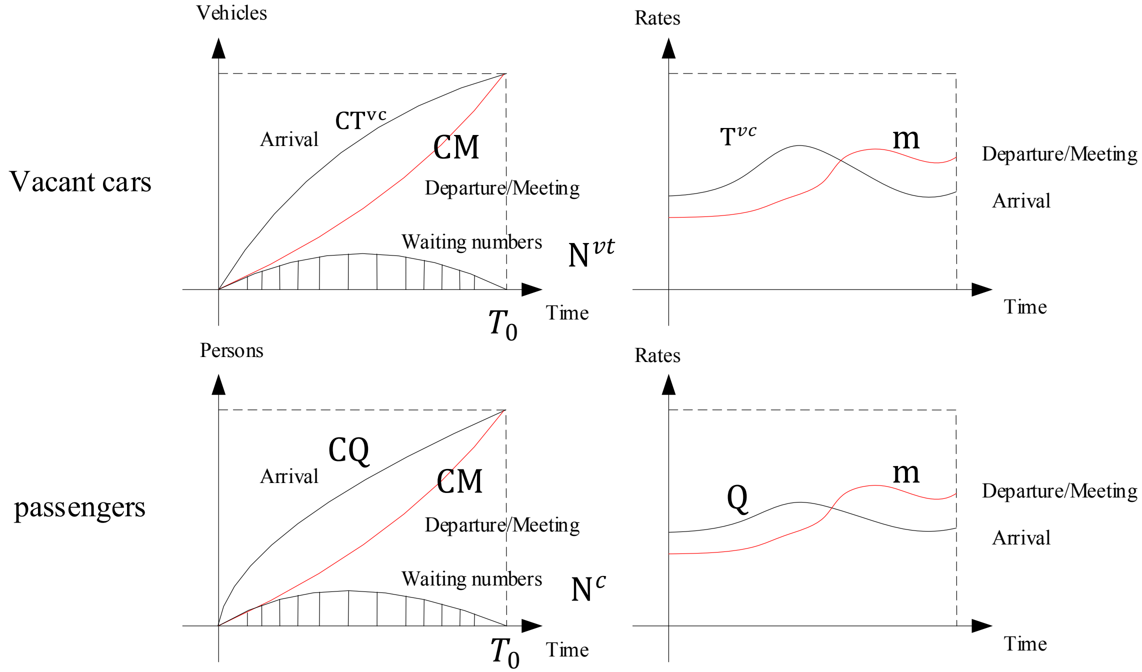

Fig. 1. Dynamic vacant car-passenger meeting model.

Matching number: $m_t = \mathrm{M}\left(N_t^p, N_t^{vc}\right)$

Vacant car number: $N_t^{vc} = \mathrm{CT}_t^{vc} - \mathrm{CM}_\mathrm{t} = \int_0^t (T_s^{vc} - m_s)ds$

Waiting passenger number: $N_t^P = \mathrm{CQ}_\mathrm{t} - \mathrm{CM}_\mathrm{t} = \int_0^t (Q_s - m_s)ds$

Where Q_t 、 T_t^{vc} are the arrival rate of passengers and vacant cars separately

[1] **Zheng H.**, Ke J., Yang H. and Chen X.* Dynamic pricing in the on-demand ride service market based on dynamic vacant car-passenger meeting model, working paper.

1.2. Pricing strategies in ride-sourcing market

A sequential decision problem with variables: dynamic pricing multiplier λ_t, commission rate η_t

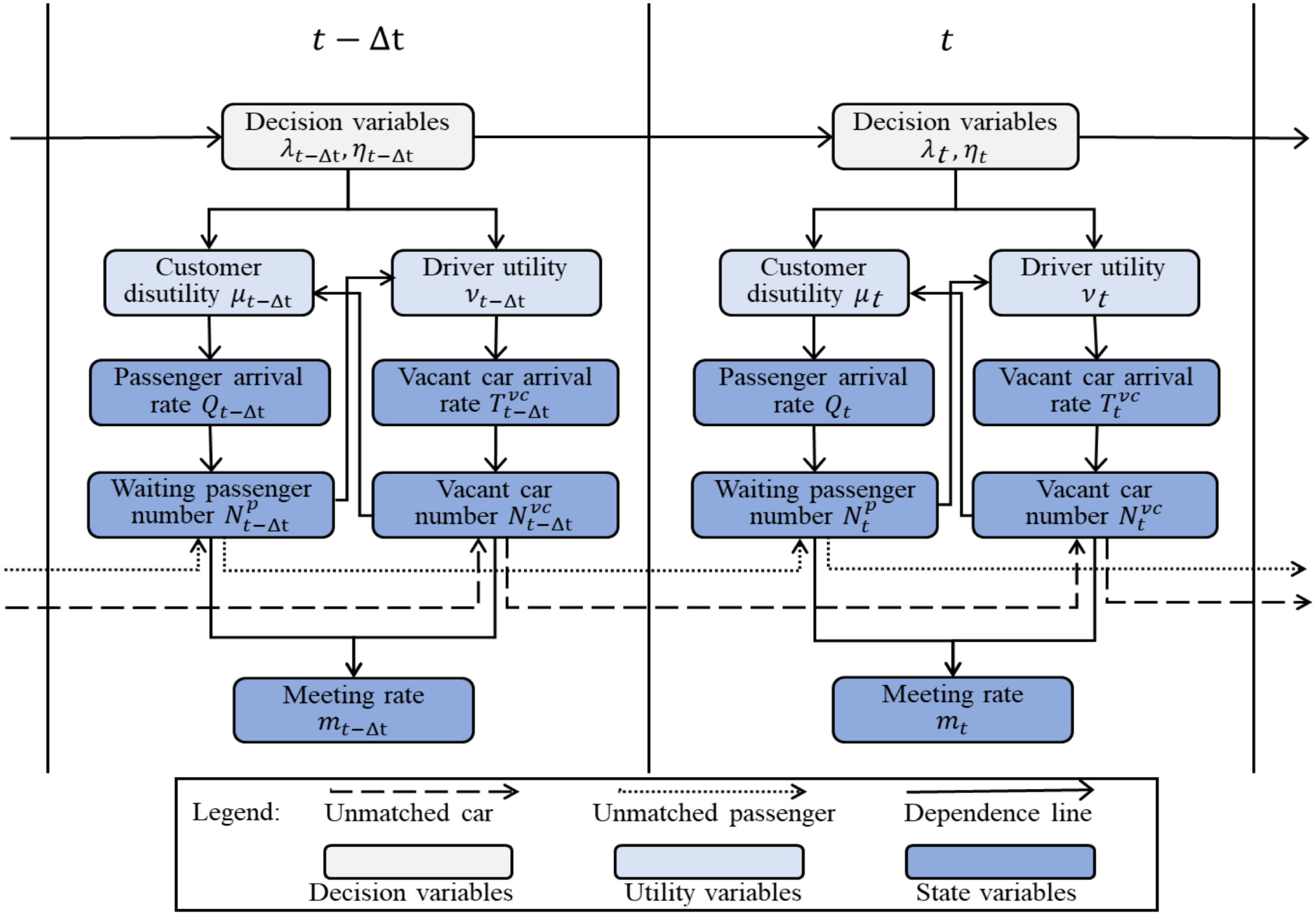

Fig. 2. The relationship between various market factors at different time intervals .

1. Economical analysis of ride-sourcing market

1.3. Solution method: Approximate Dynamic Programming

Adopted to avoid the curses of dimensionality

Learning value function approximations, iteration algorithm is shown in Table. 1

Table. 1

Algorithm 1. ADP reward value function approximation iteration algorithm
For $\forall t, n = 0$, initialize $\bar{V}_t^n = 1$
For $n = 0$ to N:
Sample demand $\overline{Q_t}$, supply $\overline{T_t^{vc}}$ for $t = \Delta\mathrm{t}$ to $\mathrm{K}\Delta\mathrm{t}$
$\alpha = 1 - 1/(2n+2)$
For $t = \Delta\mathrm{t}, \mathrm{n}\Delta\mathrm{t}, 2\mathrm{n}\Delta\mathrm{t} \ldots\ldots, \mathrm{K}\Delta\mathrm{t}$:
Solve $\tilde{V}_t(N_t^p, N_t^{vc}) = \max_{\lambda_{t+\Delta t} \cdots \lambda_{t+n\Delta t},\, \eta_{t+\Delta t} \cdots \eta_{t+n\Delta t}} \{C_t + \tilde{V}_{t+n\Delta t}(N_{t+n\Delta t}^p, N_{t+n\Delta t}^{vc})\}$
For every state:
Calculate the gradient $\hat{\boldsymbol{v}}_t^n$ at iteration n
Update VFA: $\bar{V}_t^n = (1-\alpha)\hat{\boldsymbol{v}}_t^n + \alpha\bar{V}_t^{n-1}$
State transition
Output $\bar{V}_t^{\mathrm{N}}$ for $\forall t$

Different objective functions: platform benefits and socially welfare

2. Shared mobility's impact on transportation system

2.1. Didi order data review

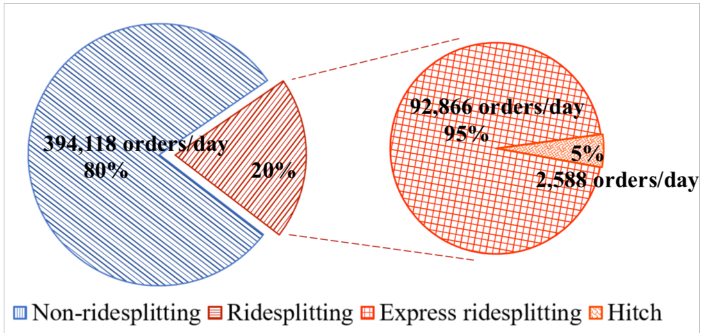

Fig. 3. Composition of ridesourcing (left) and ridesplitting (right) orders on DiDi Chuxing platform in Hangzhou, China.

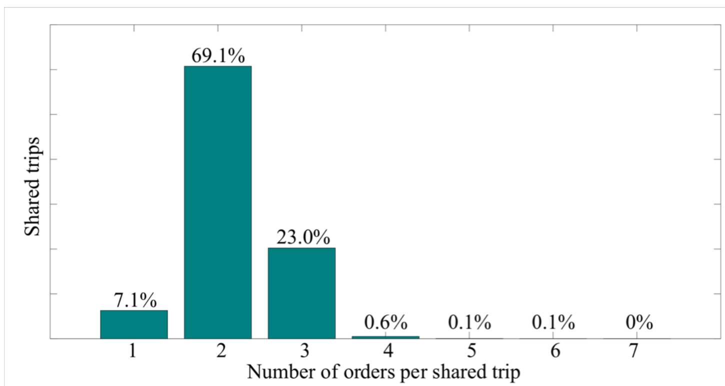

Fig. 4. Distribution of ridesplitting orders per shared trip.

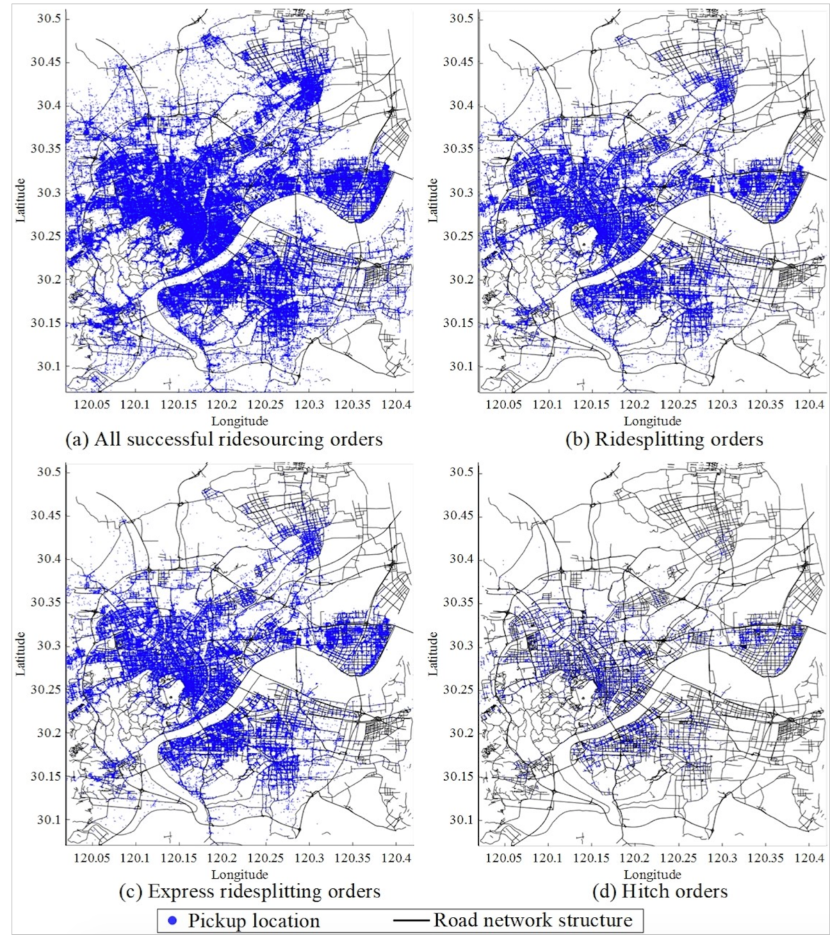

Fig. 5. Spatial distributions of pickup locations via Didi in Hangzhou, China.

[2] **Zheng H.**, Chen X. and Chen X.* (2018). How does on-demand ridesplitting influence vehicle use and purchase willingness? A case study in Hangzhou, China. *IEEE Intelligent Transportation Systems Magazine*, in press.

2. Shared mobility's impact on transportation system

2.2. Shared mobility's influence on the vehicle use and purchase willingness

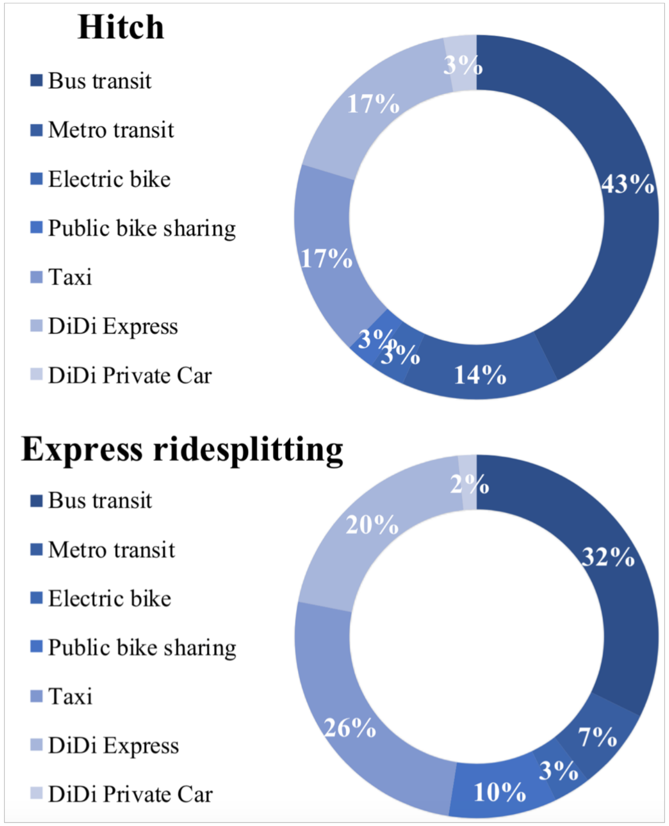

Fig. 6. Stated preference of mode choice without ridesplitting services. Hitch and express ridesplitting are two ridesplitting forms in Didi

Conclusions

At present, considering the modal shift from public transportation and non-motorized travels, shared mobility **decreases the number of road vehicles by 3,051 vehicles**. With the development of ridesplitting, more and more travelers will be attracted from using private cars or non-motorized travels, the total decreased number will be 12,327 vehicles per day in Hangzhou (**nearly 0.53% of vehicle ownership in Hangzhou**).

Ridesplitting will influence people's purchase habits and **reduce people's car purchase intention**, and further lower the vehicle ownership.

[2] **Zheng H.**, Chen X. and Chen X.* (2018). How does on-demand ridesplitting influence vehicle use and purchase willingness? A case study in Hangzhou, China. *IEEE Intelligent Transportation Systems Magazine*, in press.

3.1. Deep Learning in on-demand ride service's passenger demand prediction

Proposed a novel DL approach, called Fusion Convolutional Long Short-term Memory Network (FCL-Net)

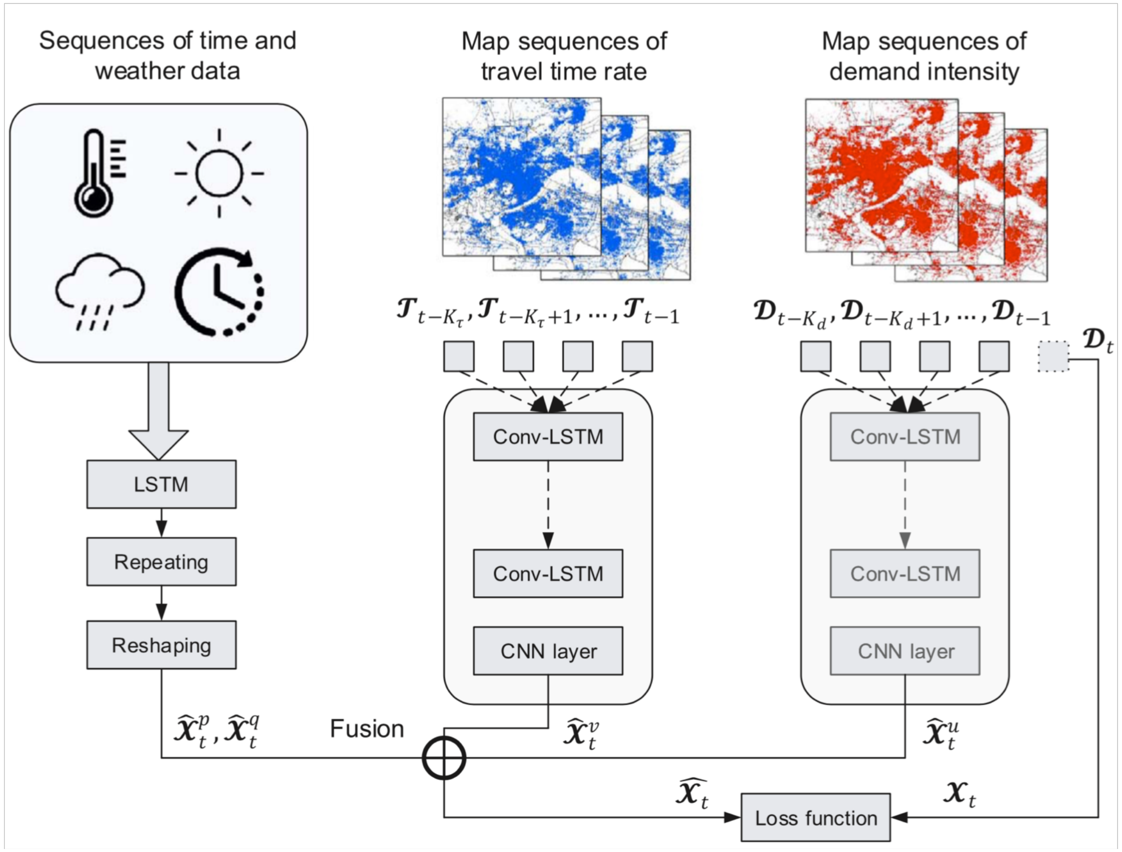

Fig. 7. Framework of the proposed FCL-Net approach.

[3] Ke J., **Zheng H.**, Yang H. and Chen X.* (2017). Short-term forecasting of passenger demand under On-demand ride services: A spatio-temporal deep learning approach. *Transportation Research Part C*, 85, 591-608.

3. Transportation system analysis

3.1. Deep Learning in on-demand ride service's passenger demand prediction

Case study

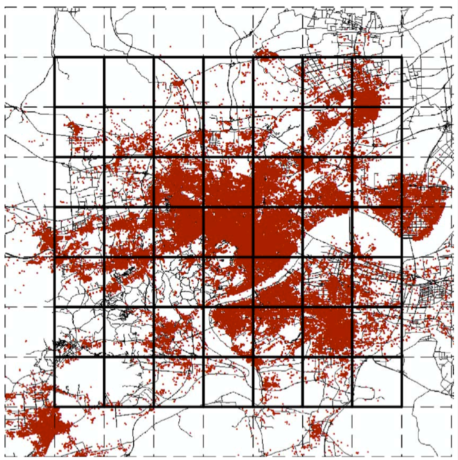

Fig. 8. The investigated region (Hangzhou, China).

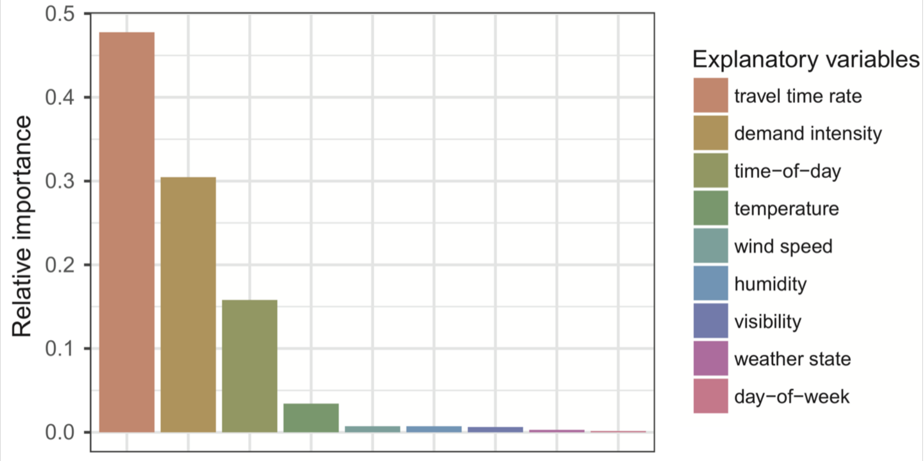

Fig. 9. Variable importance ranking.

Table 2. Predictive performance comparison.

Model	RMSE	R^2	MAE	MAPE@10[a]	Time (min)
HA	0.0378	0.736	0.0192	28.06%	0.01
MA	0.0511	0.518	0.0260	43.63%	0.01
ARIMA	0.0345	0.780	0.0178	30.40%	2.27
XGBoost	0.0322	0.801	0.0176	27.34%	2.13
ANN	0.0331	0.797	0.0198	27.95%	17.38
LSTM	0.0332	0.798	0.0172	31.27%	193.39
CNN	0.0175	0.773	0.0106	27.52%	85.42
Conv-LSTM (demand) [b]	0.0315	0.806	0.0175	26.18%	99.93
FCL-Net (selected) [c]	0.0163	0.803	0.0096	20.46%	169.90
FCL-Net (full) [d]	0.0160	0.812	0.0094	21.79%	224.71

[3] Ke J., **Zheng H.**, Yang H. and Chen X.* (2017). Short-term forecasting of passenger demand under On-demand ride services: A spatio-temporal deep learning approach. *Transportation Research Part C*, 85, 591-608.

3. Transportation system analysis

3.2. Reinforcement Learning in passenger-vehicle matching problem

A searching tree structure is built to describe the matching problem in on-demand ride services.

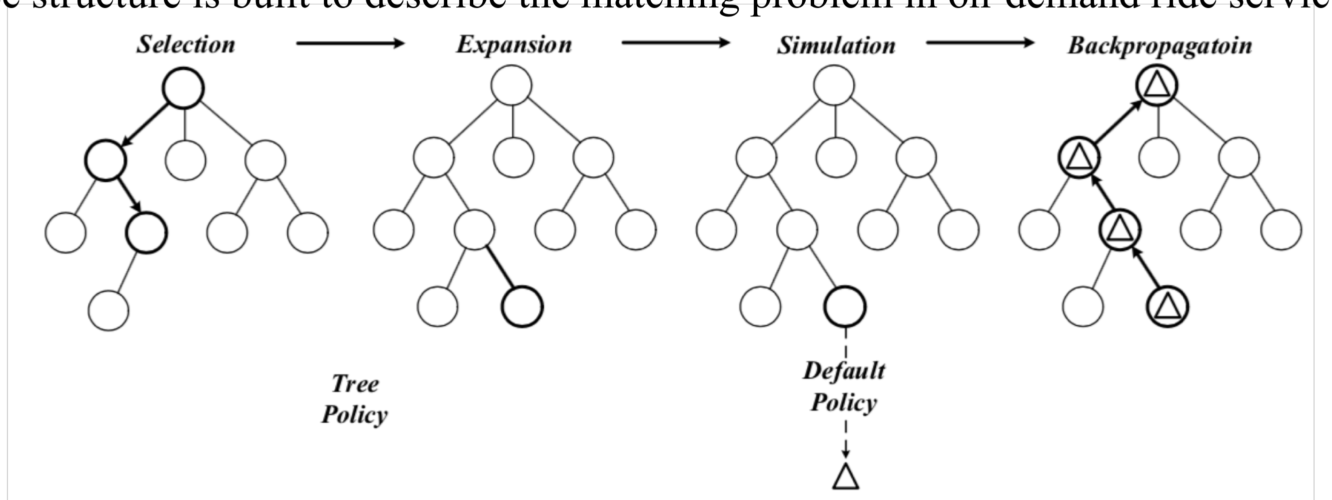

Fig. 10. An illustration of Monte-Carlo Tree Search (MCTS) procedures.

Table 3. MCTS algorithm for passenger-vehicle matching problem.

Initialization: Create root node m_0 with state s_0.
For *i* in 1,2,3…and the height of the tree structure **do**
  While within computational *Budget* **do**
    Initialize the UCB value of each subnode with zero;
    Select the best child node with biggest UCB value (same then random choose);
    Expand the chosen node to the terminal of the tree structure with a random choice;
    Calculate the total waiting time of the matching plan;
    Update every node's state during the expansion process.
  End while
  Select the best leaf node as the new root node m_0.
End for
Output: Connect all the best leaf nodes as the final result.

3.3. Machine Learning in short-term traffic speed prediction

Introduce spatial and temporal parameters into Random Forest and Support Vector Regression models

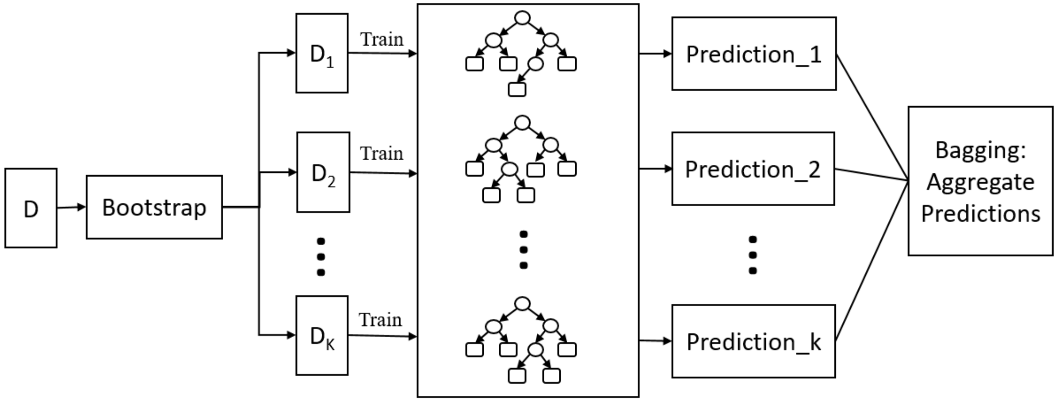

Fig. 11. Random Forest (RF) algorithm.

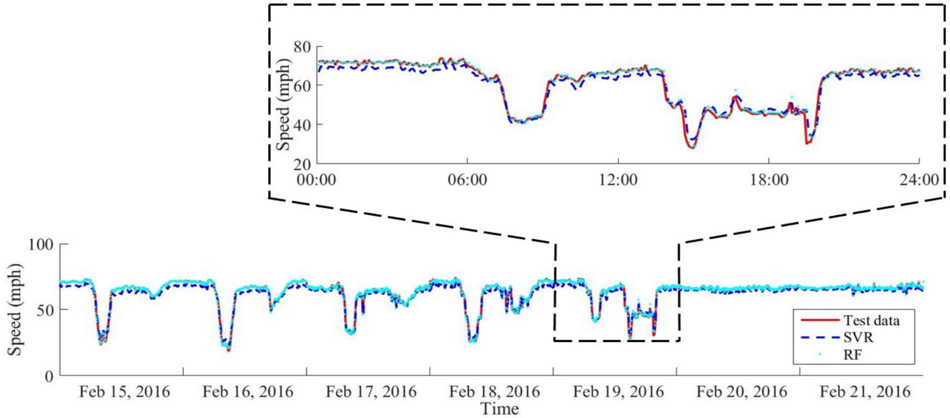

Fig. 12. Short-term traffic speed prediction using from PeMS

[4] **Zheng H.**, Chen X. and Chen X.* (2017) Random forests for freeway short-term traffic speed prediction. *The 17th COTA International Conference of Transportation Professionals*, Shanghai, China, July 7-9, 2017.