

Introduction

This study examines the pattern of refueling activities based on vehicle space-time path by using taxi GPS trajectory data to help optimize gas station location and improve energy supply efficiency.

Existing refueling activity studies focus on site selection of refueling infrastructures and fuel economies. However, few studies focus on the patterns of vehicles' refueling activities. Meanwhile, identification of refueling activity patterns help optimize gas station location and reduce fuel consumption.

The characteristics of refueling activities were mostly studied through survey. Survey can provide detailed information on refueling activities at micro-level but fails to reveal the refueling activity patterns at macro-level due to their small sample sizes. Besides, the collection of survey samples can be costly and time-consuming, which limits the sample size and sample use in understanding refueling activity patterns.

We seek to analyze refueling activities at macro-level based on the time-geographic framework by using GPS trajectory data.

Methodology

Space-time paths as well as spatial locations can be represented using the 3-D space-time coordinates, as Fig. 1 shows.

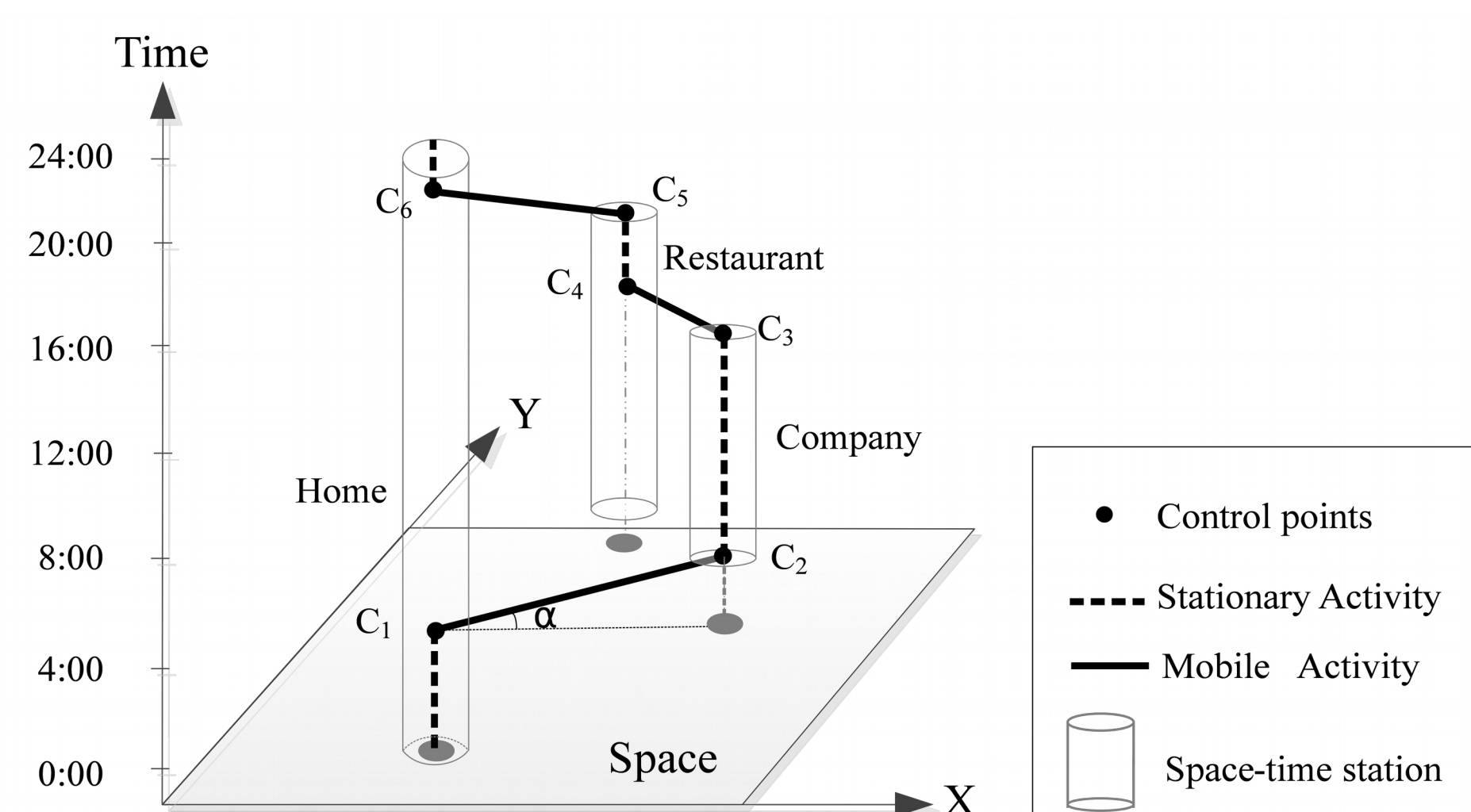


Fig. 1 3-D space-time coordinates and individual space-time path

For an individual m on an isotropic plane, the space-time path consists of a sequence of control points and path segments connecting the control points. Each control point, c_i , consists of a tuple:

$$c_i = \langle Loc_i, t_i \rangle \quad (1)$$

$$s_{ij} = \langle c_i, c_j \rangle \quad (2)$$

where Loc_i is the location and t_i the timestamp. The space-time path segment s_{ij} between adjacent control points c_i and c_j is a straight-line segment:

It is assumed that the individual is moving at a constant speed in each space-time path segment. Therefore, the speed of the path segment s_{ij} is :

$$v_{ij} = \frac{\|Loc_j - Loc_i\|}{t_j - t_i} \quad (3)$$

where $\|Loc_j - Loc_i\|$ is the Euclidean distance between c_i and c_j . If the instantaneous velocity of each control point v is recorded, average acceleration a_{ij} of a space-time path segment can be calculated by:

$$a_{ij} = \frac{v_j - v_i}{t_j - t_i} \quad (4)$$

We can identify a stationary activity using a vertical segment of the space-time path (as shown in Fig. 1). Space-time stations can also be identified by vertical line segments of 3-D space-time paths, allowing for the incorporation of temporal component of activity locations. A space-time station Q^r can be defined as:

$$Q^r(t) = Loc^r, \forall t \in [L, [L] \dots] \quad (5)$$

Equation (5) shows that a station activity can be identified based on segments of space-time paths. A mobile activity (MA) and a stationary activity (SA) can be defined by:

$$MA = \{(Loc(S), T_s), (Loc(E), T_e), S\} \quad (6)$$

$$SA = \{(Loc(S), T_s), (Loc(E), T_e), S \mid |Loc(E) - Loc(S)| < \delta\} \quad (7)$$

where $Loc(S)$ and $Loc(E)$ are locations of the start and end points of activities, T_s is the start time and T_e is the end time, and S is the space-time path segment between the start and end points of the activity. Besides, by taking recording errors into account (e.g., GPS points tend to drift around the actual location when the GPS unit is stationary), a stationary activity requires the distance between the start point and the end point $|Loc(E) - Loc(S)|$ to be less than a threshold δ .

This study analyzes the characteristics and features of vehicles' refueling activities, including distance feature (F_D), temporal feature (F_T) and moving feature (F_M), based on individual space-time paths built from vehicles' GPS traces. Fig. 2 illustrates the refueling activity identification process.

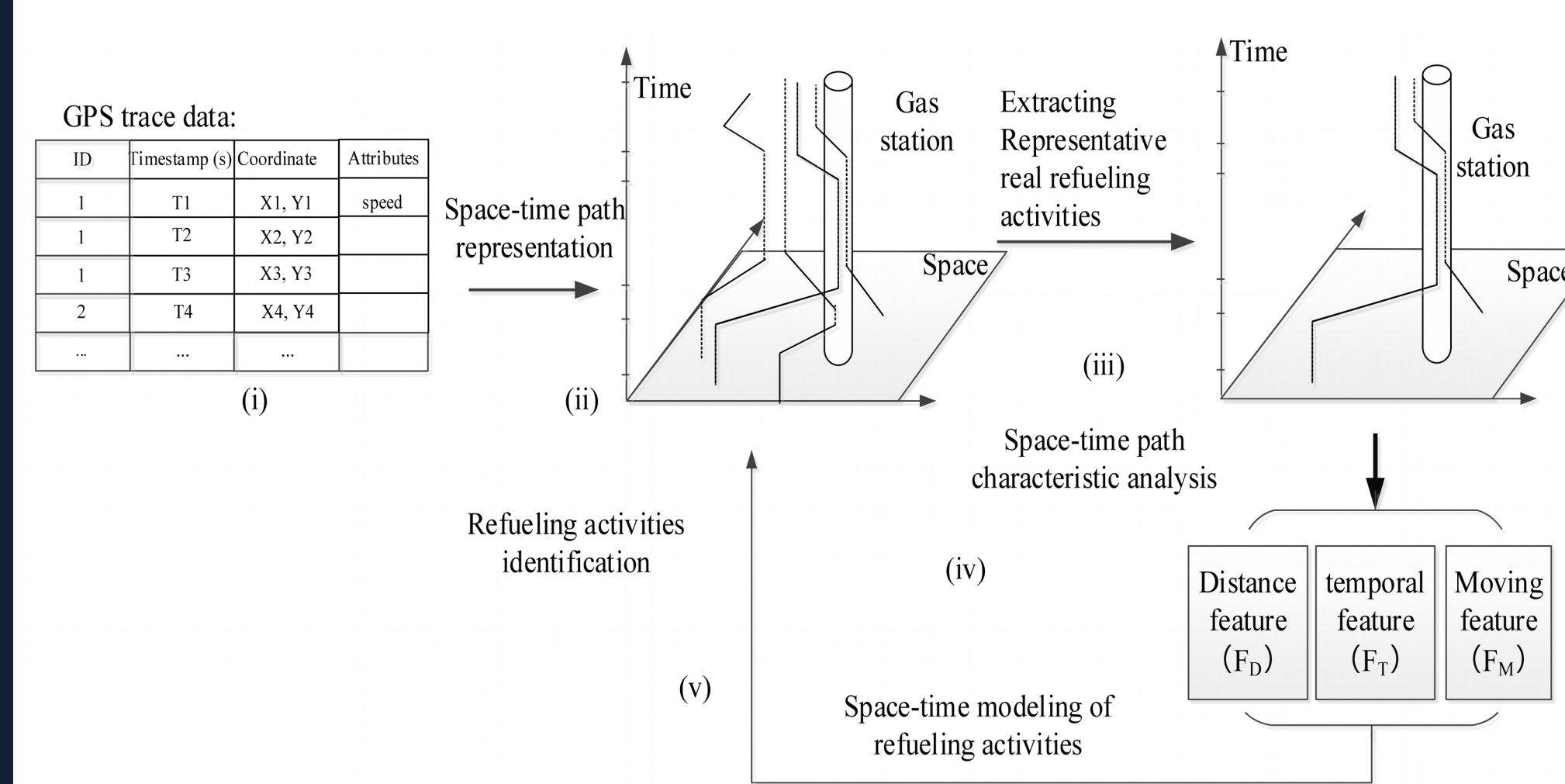


Fig. 2 Refueling activity identification process

As Fig. 2 demonstrates, this study analyzes the space-time characteristics and patterns of refueling activities from vehicles GPS data (Fig. 2 (i)). We construct the space-time paths from GPS data (ii) and extract a sample of the space-time paths representing actual refueling activities (iii). Afterwards, we analyze the characteristics of the space-time paths of the real activities, and use distance feature, temporal feature and moving feature (iv) for describing and defining refueling activities. Finally, we identify the activities from individual space-time paths based on the three features (v).

The segment of a space-time path that represent a refueling activity and a stay in a gas station is shown in Fig. 3(a), in which the red vertical line segment denotes the refueling activity. Fig. 3(b) and 3(c) are 2-D projections of the space-time path of the refueling activity on the spatial dimension and its 1-D projection on the time dimension.

To analyze the space-time characteristics and patterns of refueling activities, we first implement dimension reductions to the space-time paths. Then we define three space-time features: (1) F_D (i.e., distance from gas stations); (2) F_T (i.e., activity duration); and (3) F_M (i.e., travel speed) to define refueling activities, which can be calculated as geometric features in the individual space-time path, as Fig. 3(a), (b) and (c) show.

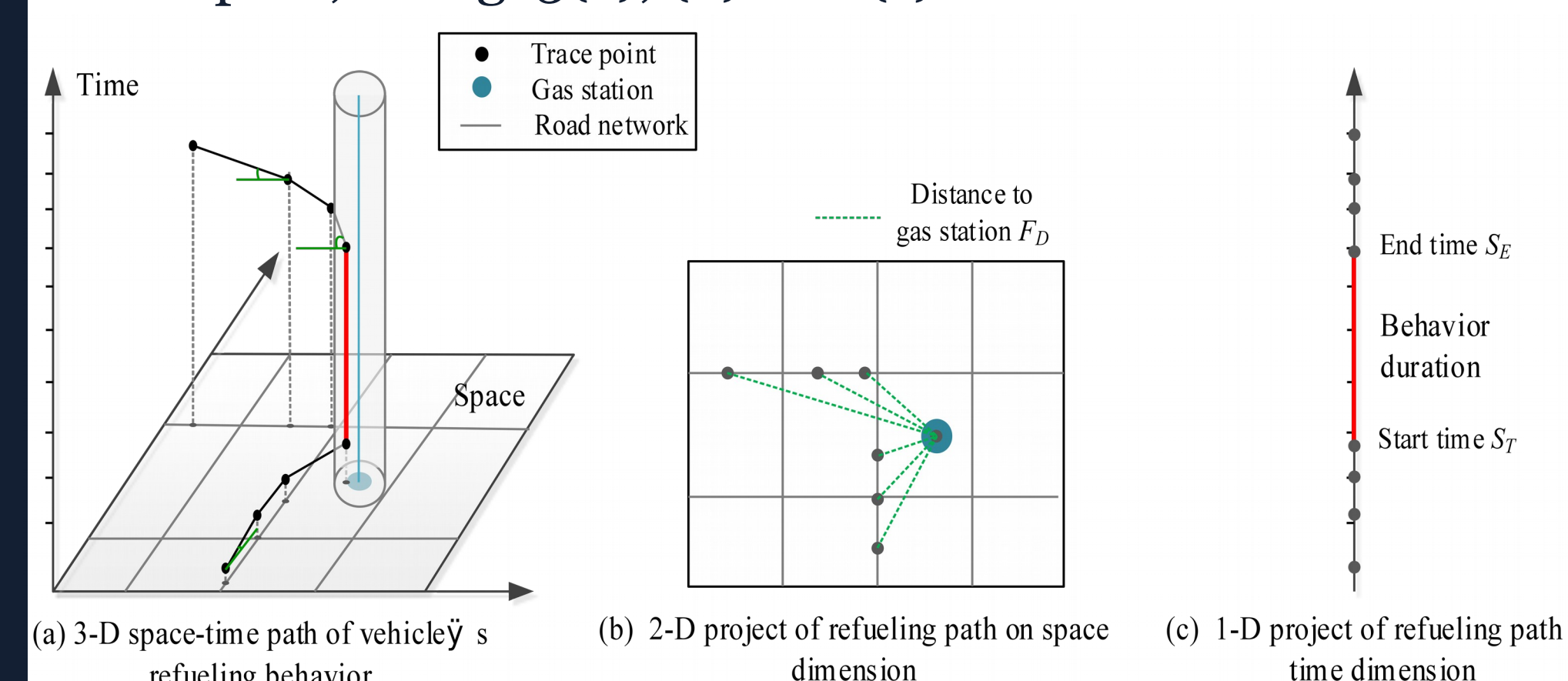


Fig. 3 3-D space-time path of refueling activity and its projects on space and time dimensions

Case Study

We use taxi GPS trajectory data collected from 6,869 taxis on July 31, 2015 in Wuhan, China. The taxi GPS trajectories are sampled at a fixed time interval of 40 s, with a position accuracy of approximately 15 m. The Wuhan road network and all 59 gas stations in the city are shown in Fig. 4

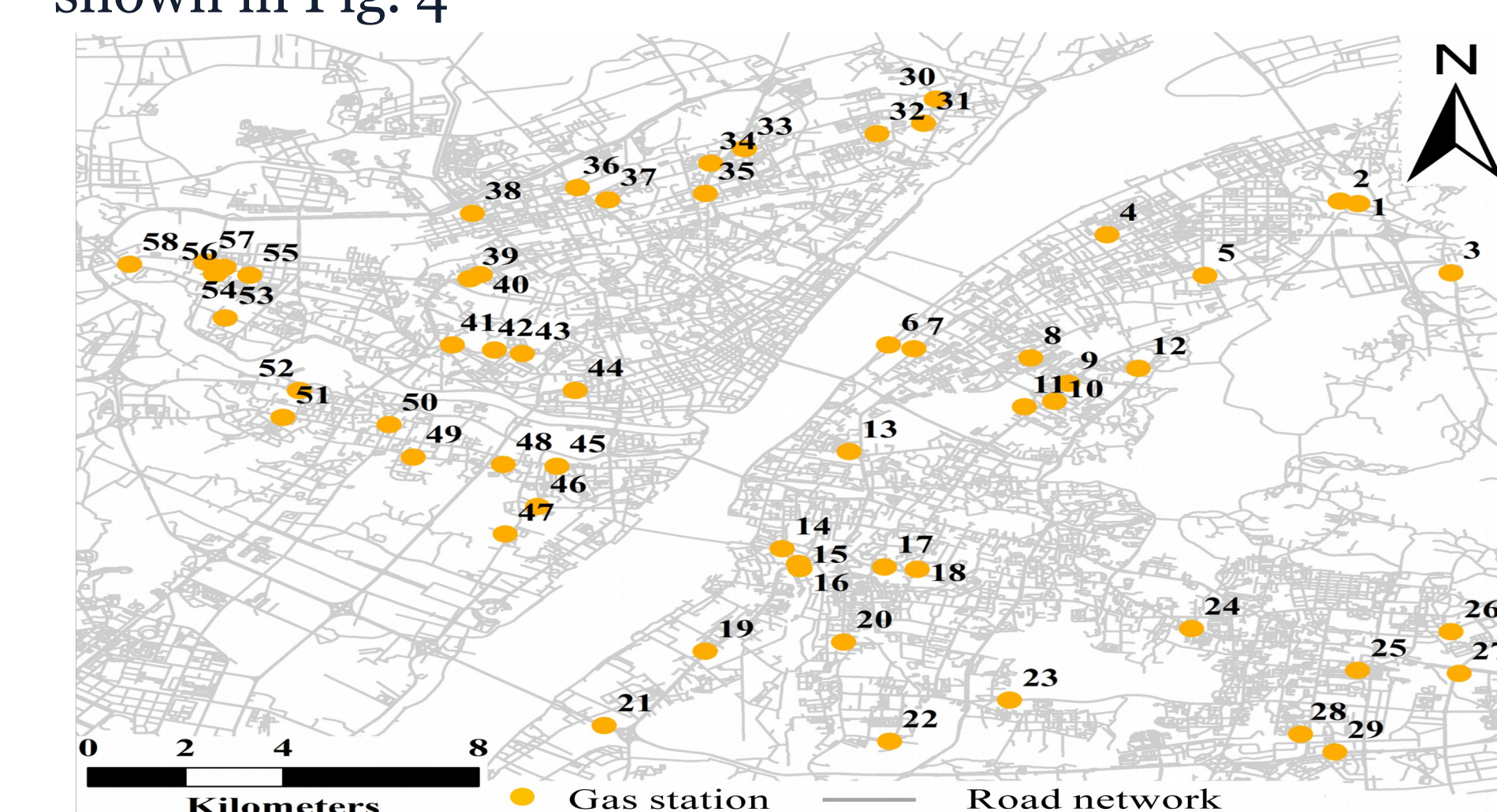


Fig. 4 Road network and gas station distribution in Wuhan

We first extract 162,643 stationary activities with duration between 3 minutes to 1 hour.

Then, we label 2,522 stationary activities. 1,261 real refueling activities and 1,261 non-refueling activities are taken as samples to train a SVM classifier.

The identification results are evaluated by cross validation with the other 1,261 real refueling activities. The accuracy and recall of the identification results are 93.3% and 99.9%, respectively.

We apply the SVM classifier in detecting the refueling activities from the GPS trajectories of the 6,869 taxis, and finally obtain 18,064 refueling activities.

The space-time distribution of these detected refueling activities is shown in Fig. 5

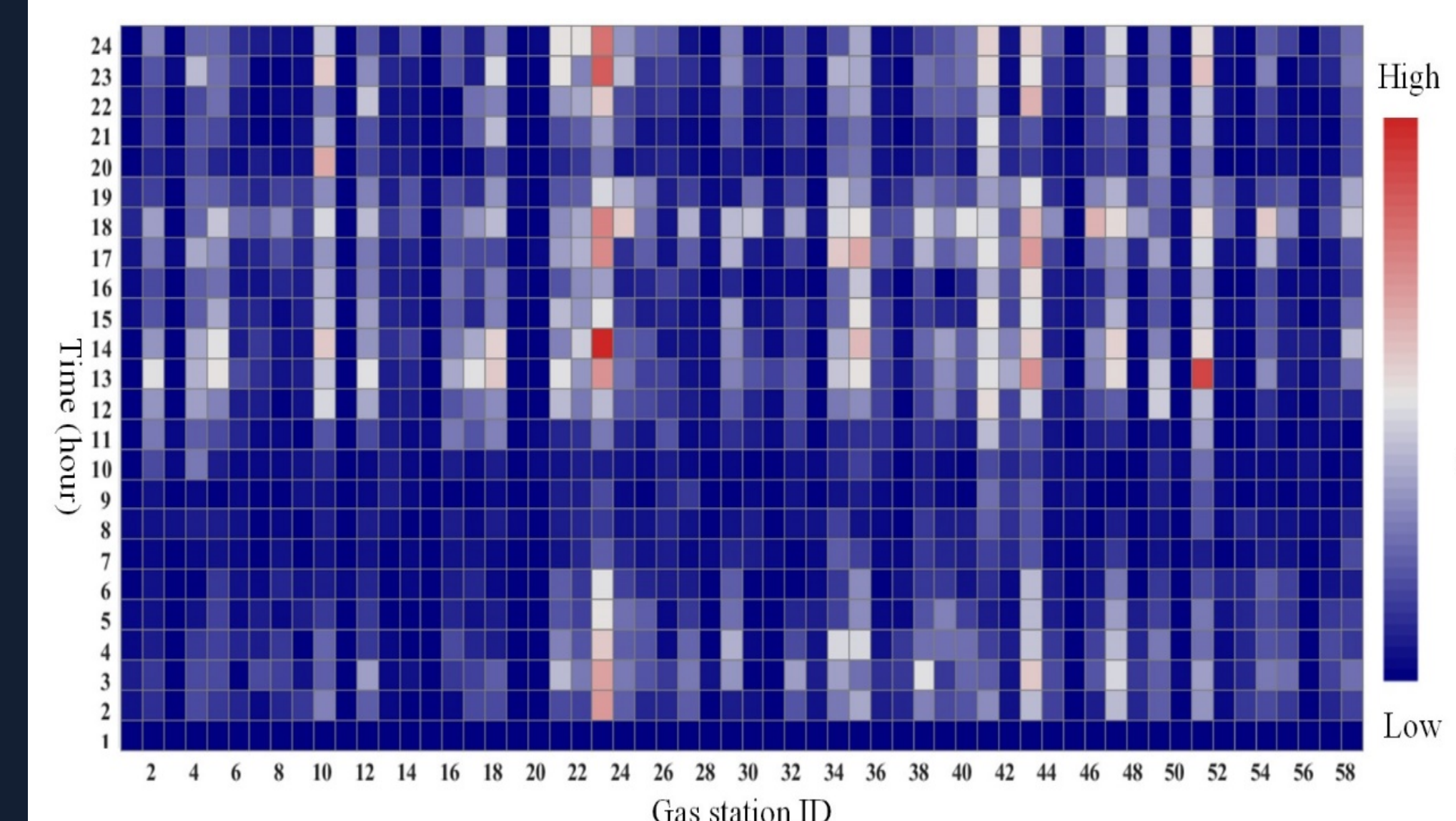


Fig. 5 illustrates the space-time distribution of the refueling activities of taxis, which reveals the distinctive spatial and temporal patterns of refueling activities.

Discussion and Conclusion

Our study proposes a novel approach for identifying vehicles' refueling activities based on space-time path.

As the traditional approaches for studying refueling activities heavily rely on the time-consuming and costly travel surveys, the collected information is often not adequate for understanding large-scale citywide refueling activity patterns.

Since rapid urbanization is accompanied by the expansion of urban transportation, an alternative low-cost and expedient approach for identifying refueling activities and their space-time patterns would be helpful for the improvement of energy supply efficiency. Better gas-station planning is also beneficial in both economic and environmental senses.