5 Experimental Results

5.1 Experimental Setup

This section presents the experimental results that demonstrate the feasibility of applying the proposed algorithm. The algorithms were implemented in C++ and the experiments were run on an Intel Core i7 2.3 GHz PC with 8GB main memory and Ubuntu Linux system. We examine Reverse Nearest Neighbourhood on road networks queries on real-world road network graphs.

Table 2 Dataset characteristic

<table>
<thead>
<tr>
<th>Description</th>
<th>Density level</th>
<th>Users</th>
<th>Facilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Map A: University campus area</td>
<td>Low</td>
<td>60</td>
<td>12%</td>
</tr>
<tr>
<td>Map B: A medium-sized city</td>
<td>Medium</td>
<td>690</td>
<td>3%</td>
</tr>
<tr>
<td>Map C: Densely populated of suburbs</td>
<td>High</td>
<td>1864</td>
<td>3%</td>
</tr>
</tbody>
</table>

We evaluate our proposed algorithm by simulating scenarios ranging from low-density to high-density in terms of the number of objects in road networks. The network covers all types of roads, including local roads and contains real edge weights for travel distances. We conduct in-depth studies based on datasets for a university campus (low density), a medium-sized city and a densely populated group of suburbs (high density). These datasets are listed in Table 2.

Table 3 Experiment Parameters

<table>
<thead>
<tr>
<th>NH Parameter</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$ (km)</td>
<td>0.1, 0.3, 0.5, 1, 1.5</td>
</tr>
<tr>
<td>$m$</td>
<td>2, 4, 6, 10, 16</td>
</tr>
</tbody>
</table>
In our experiments, we use the term ‘Low-Density’ if the number of objects is less than one hundred; we use ‘High-Density’ if the number of objects is greater than one thousand [54]. ‘Medium-Density’ is used when the number of objects deemed to be between one hundred and one thousand. The purpose of our experiments is to show how different factors such as the number of objects determining density and value of \( d \) and \( m \) could affect the results of our algorithm in terms of the number of queries obtained, the number of neighbourhood members, and the size of the neighbourhood.

In this paper, several evaluations of the proposed algorithm’s flexibility and the correctness and accuracy of results are studied to examine the results of the experiments. We evaluate the isolated points of interest and the flexibility of our proposed algorithm to show their tolerance to the constraint of neighbourhoods compared to the Voronoi cell based on the Reverse Nearest Neighbour (RNN) algorithm, and the proposed algorithm is proven to be not mutually exclusive. Also, to evaluate the accuracy of the results and our approach’s effectiveness, we compared the Euclidean and road network outcomes to evaluate the effectiveness of our approach to road network queries. We proved that our results are more reliable because they are based on real datasets. Table 3 presents the parameters applied to RNNH-RN queries in the experiments.

![Fig. 8 Monash University -Clayton Campus-](image)

5.2 Low density Experiment

In this experiment, we use the Monash University Clayton campus and residential area as the dataset. We focus on the campus environment which consists of a low-density dataset to test the algorithm with a variety of values for maximum road networks distance (\( d \)) and the minimum number of neighbourhood members (\( m \)) value (e.g. low \( d \) and high \( m \) value ).
This dataset has approximately 6600 edges and 8100 vertices, and comprises a complex of fifty-two shops and stores. The dataset has an area of 5.20 km², as shown in Figure 8. We evaluate the range of maximum road network distance (d value) and a minimum number in the neighbourhood to determine their impact on the number of queries obtained, the number of neighbourhoods and the size of neighbourhoods members concerning each result of the RNNH-RN algorithm.

Table 4 Experimental Analysis for Nearest Neighbour - Monash University-

<table>
<thead>
<tr>
<th>Distance from</th>
<th>Number of shops</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-100 m</td>
<td>34</td>
</tr>
<tr>
<td>200-300 m</td>
<td>2</td>
</tr>
<tr>
<td>300-400 m</td>
<td>7</td>
</tr>
<tr>
<td>400-600 m</td>
<td>7</td>
</tr>
<tr>
<td>600-700 m</td>
<td>2</td>
</tr>
<tr>
<td>700 m - 800 m</td>
<td>2</td>
</tr>
<tr>
<td>800 m - 900 m</td>
<td>2</td>
</tr>
<tr>
<td>above 1 km</td>
<td>4</td>
</tr>
</tbody>
</table>

The maximum distance : 2.11 km
Average distance to nearest shop: 0.3011 km

In this study, we conduct extensive geospatial analysis to achieve a comprehensive understanding of a low-density dataset behaviour. We calculate the network distance from each point of interest (POI) to the nearest neighbour, as shown in Table 4. In the graph, the nearest neighbour’s average network distance is 0.3 km and the maximum network distance to the nearest neighbour is 2.11 km. The total road network distance to the nearest neighbour in the graph is 16 km. As shown in Table 4, most points of interest are less than 100 m to the nearest neighbour, and only four points of interest have more than 1 km road network distance to the nearest neighbour.

Figure 9 shows the difference between and compares the outcome Euclidean distance and of road networks, for the RNN query and reverse nearest neighbourhood (RNNH) query for the purple query. The RNN query and the RNNH query for the purple query. The result of the RNN query for Euclidean distance is different from that obtained for road network distance: it has almost the same number of neighbourhoods, but it has different neighbourhood members as shown in Figure 9 (a) and Figure 9 (b). Based on the spatial network, the travelling distance would be much further. Figure 9 (c) displays an example of Euclidean reverse nearest neighbourhood that returns two neighbourhoods (five and three members), which differs from the reverse nearest neighbourhood on the road networks query which returns the results for two neighbourhoods (six and three members). The first neighbourhood has six members on road networks. The Euclidean RNNH does not involve the sixth point because the Euclidean distance from the competitor facility’s point is a shorter distance to the query point. Figure 9 (d) shows the results of the RNNH-RN purple query pertaining to two neighbourhoods (depicted by circle and triangle).
Fig. 9 Spatial Query results on Map A

Fig. 10 RNNH-RN Query Result for $d = 0.5km$
In terms of the minimum value in the neighbourhood (m), when the value changes and increases from 4 to 6, the result excludes one neighbourhood based on the query preferences as shown in Figure 10. Our findings also show how the result changes according to the d value as depicted in Figure 11. Figure 11 (a) shows an example of reverse nearest neighbourhood query when the maximum road distance between neighbourhoods is 0.300 km: it returns one neighbourhood. It excludes the points that are more than 0.300 km distant from neighbourhood members.

We studied the behaviour of the reverse nearest neighbourhood on road networks (RNNH-RN) with low density, varying the value of the maximum network distance between neighbourhood members (d), and the minimum number of neighbourhood members (m). First, we studied the effect of the d factor on the algorithm. Specifically, Figure 12 shows the number of queries obtaining neighbourhood and the average of neighbourhood members in each neighbourhood for varying values of (m). Figures 13 (a) shows the number of queries that obtain results for the RNNH-RN algorithm. When the maximum road distance (d) between neighbourhood members is less than 1 km, only two queries obtain the RNNH-RN result, increasing to three queries when \(d = 1.5\) km. This is because RNNH-RN is obtained depending on the closeness of points of interest in forming the neighbourhood. Therefore, the chance of obtaining a query result improves when \(d\) increases.

Our report shows displays the average number of neighbourhoods in each query; we find that the average number of neighbourhoods is one neighbourhood when the maximum network distance is between 0.100 and 0.300 km, and increases to two neighbourhoods when the maximum network’s distance increases.

We also study the effect of the minimum neighbourhood number of members (m) in the low-density dataset. We that, generally, when the value of \(m\) increases, the number of queries for neighbourhood decreases dramatically, and the average number of neighbourhoods decreases. The reason for this is that when the minimum number of neighbourhood members increases, neighbourhoods with a small
(a) Number of Queries with RNNH  
(b) Number of Queries without RNNH  
(c) The average number of neighbourhoods

Fig. 12 Variety of $d$ value

(a) Number of Queries with RNNH  
(b) Number of Queries without RNNH  
(c) The average number of neighbourhoods

Fig. 13 Variety of $m$ value

(a) The number of points belonging to only one neighbourhood  
(b) The number of points belonging to more than two neighbourhoods  
(c) The number of points not belonging to any neighbourhood  
(d) The average number of neighbourhood members

Fig. 14 Analysis for Monash University campus
The number of NH members

Minimum number of NH member

RNNH-RN Algorithm

55
37
32
26
26

RNNH Algorithm

50
33
28
26
26

(a) m value

Fig. 15 Comparison RNNH and RNNH-RN algorithm for Monash University campus

number of members are excluded.

Figures 14 illustrates the average number of neighbourhood members, the number of points belonging to one neighbourhood and the number of points belonging to more neighbourhoods. The number of neighbourhoods increases dramatically when the \( d \) value is increased. This is unlike the number of points not belonging to any neighbourhood where the number decreases incrementally with an increase in the \( d \) value.

Figure 15 shows a comparison between a reverse nearest neighbourhood in Euclidean distance and road networks to show road networks’ accuracy. In Figure 15 (b), we see the effect of different values of \( m \) and \( d \). It is clear that for both, the number of neighbourhood members decreases dramatically with an increase in \( m \). This is because there is a correlation between the number of neighbourhood members and the \( m \) value: when \( m \) increases, neighbourhoods that do not satisfy the \( m \) value are excluded. We also find that the RNNH-RN query processing algorithm’s efficiency in road networks improves when the \( d \) increases and the neighbourhood members in Euclidean RNNH are fewer than RNNH-RN in road networks. This is because, for each query, the Euclidean distance from a point to competitor facilities is mostly shorter compared to the distance in road networks, which also increases the number of neighbourhood members.

5.3 Medium density Experiment

In this experiment, we use a spatial database of Melbourne city as the dataset. Melbourne is located on the south coast of the state of Victoria, Australia, and it is divided into two parts, with a medium density of roads in the centre, and light density on the western and eastern sides. For this experiment, we use the main roads that connect the western and eastern points. We use the supermarkets’ dataset for Melbourne, represented by the grey dots in Figure 16.

By means of a graph, we conduct a geospatial analysis of the nearest points, which are shown in Table 5. There are 350 points with a network distance of less
than 0.100 km to the nearest point, and there are thirty-five points of interest (POIs) between 0.100 km and 0.200 km, and thirty-eight points of interest between 0.200 km and 0.300 km.

Also, twenty-five points are between 0.300 km and 0.500 km, and forty points are between 0.500 km and 0.800 km. There are two hundred and sixty points that are more than one km from the nearest neighbour. The average distance to the nearest point is 750 m. The graph shows that the total network distance travelled to the nearest neighbour is 2092 km. Tables 5 gives more details about the experiment conducted for Melbourne city.

In this study, we randomly select the location of queries on different sides. They are marked by stars, as shown in Figure 17, and we take the four queries (blue, pink, yellow, green stars) as examples to explain our findings and observations. Figure 17 (a) shows the Euclidean Voronoi diagram (VD) for four facilities and the RNN query outcome for the blue query. At the same time, Figure 17 (b) presents the network Voronoi diagram (NVD). The RNN in the road network excludes several points, and the road network takes into consideration the road distance,

### Table 5 Experimental Analysis Nearest Neighbour -Melbourne City-

<table>
<thead>
<tr>
<th>Distance from</th>
<th>Number of shops</th>
</tr>
</thead>
<tbody>
<tr>
<td>1- 100 M</td>
<td>350</td>
</tr>
<tr>
<td>100-200 M</td>
<td>29</td>
</tr>
<tr>
<td>200-300 M</td>
<td>38</td>
</tr>
<tr>
<td>300-500 M</td>
<td>23</td>
</tr>
<tr>
<td>500-800 M</td>
<td>30</td>
</tr>
<tr>
<td>800m - 1 km</td>
<td>14</td>
</tr>
<tr>
<td>above 1 km</td>
<td>206</td>
</tr>
</tbody>
</table>

The maximum distance : 70 km

Average to nearest shop: 0.750 km
which is somewhat greater than the Euclidean distance. The blue neighbourhood member belongs to the blue query, the yellow neighbourhood belongs to the yellow query, and the pink neighbourhood belongs to the pink query.

We can see that the results are different because Euclidean distance does not account for obstacles (such as a lake). Consequently, the result of reverse nearest neighbourhood (RNNH) when \( d = 0.500 \) km and \( m = 4 \), will also differ between the road network distance and the Euclidean distance as shown in Figure 17 (c) and Figure 17 (d).

In terms of the number of neighbourhoods is obtained by queries, both Euclidean and network distance obtain two neighbourhoods when the \( d = 0.500 \) (circle and triangle neighbourhood), but the neighbourhood members are different. Also, we see that the number of neighbourhood (NH) members in each neighbour-
Fig. 18 Green POI belongs only one NH, red POI belongs two NHs, Melbourne City

hood are different as shown in Figure 17.

Figure 18 shows our proposed algorithm’s flexibility with different $d$ values, and the $m$ value equals four. The red points belong to two queries, the green points belong to only one query, and the grey points do not belong to any query. It is obvious that the RNNH-RN algorithm is not mutually exclusive; hence, the neighbourhood members can belong to two neighbourhoods for two queries, as shown in Figure 18. Figure 18 (a) and Figure 18 (b) show the result of RNNH-RN when the $d = 0.300$ and $d = 0.500$ km. The results of RNNH-RN show that for the points belonging to one neighbourhood, the number of neighbourhood members increases when the $d$ value increases. In Figures 18 (c) and 18 (d), the number of red points that belong to more than the query increases when the $d$ value increases.

In terms of the minimum value in the neighbourhood $(m)$, we study the effect number of $m$ value. When the value changes and increases from two to four, we find that the result excludes one neighbourhood based on the query preferences. The orange query result has three neighbourhoods: represented by a diamond, circle and triangle (two, four and six neighbourhood members respectively), when the $m$ value equals two as shown Figure 19 (a). On the other hand, Figure 19 (b)
computing reverse nearest neighbourhood on road maps 23

Fig. 19 RNNH-RN Query Result for \( d = 0.5 km \)

(a) \( m = 2 \)

(b) \( m = 4 \)

Fig. 20 RNNH-RN Query Result for \( m = 4 \)

(a) \( d = 0.300 \)

(b) \( d = 0.500 \)

presents an example of the reverse nearest neighbourhood query when the \( m \) value equals four. We observe that it returns only two neighbourhoods (shaped as circle and triangle) but excludes the neighbourhoods that do not satisfy the minimum number of neighbourhood members. Figure 19 illustrates the effect of the \( m \) value on RNNH-RN queries.

As shown in Figure 20, the results change according to the value. Figure 20 (a) depicts an example of the reverse nearest neighbourhood on road networks (yellow query) when the \( d = 0.300 km \). It returns one neighbourhood with seven members located close to each other within 0.300 km. In Figure 20 (b), when the maximum network’s distance is 0.500 km, the yellow query involves the other two members that have a road network distance of less than 0.500 km and more than 0.300 km from the neighbourhood.

We report the result of the reverse nearest neighbourhood on road networks (RNNH-RN) based on the query points with different maximum distance values.
(d) and minimum values in the neighbourhood (m). The study illustrates how many queries could obtain RNNH-RN with varying maximum distances between neighbourhood members in increments of 0.100, 0.300, 0.500, 1 and 1.50 km as depicted in Figure 21 (a). Figure 21 (b) shows how many queries do not obtain neighbourhoods; it is clear that when the maximum distance value increases, there is a stronger possibility of obtaining a neighbourhood.

In terms of the number of neighbourhoods obtained, we report the number of neighbourhoods obtained for each query with different maximum distance values (d), which increases when the maximum road distance increases. The average number of neighbourhoods increases to three when the maximum network distance reaches 0.500 km as indicated in Figure 21 (c). The reason for this is that when the maximum distance (d) increases, it in turn, increases the chance of obtaining more points of interest in the neighbourhood. Therefore, there is a better chance of obtaining a query result improves, when the maximum distance between NH members increases.

Our experiment results led to the following conclusions. When the maximum distance (d) between the neighbourhood members increases, the possibility of obtaining more neighbourhoods increases dramatically. Whether or not an RNNH-RN neighbourhood is obtained depends on the closeness of points of interest to each other. Moreover, the location of the Network Voronoi Diagram of a query is limited by the location of other competitor facilities, which can limit the number of the neighbourhoods obtained.

Conversely, when the value of m increases, the number of queries obtaining NH decreases dramatically as shown in Figure 22. Also, we find that the average number of neighbourhoods decreases, when the values of m increases. This is because there is a small group of points in the result set when m decrease. In our study, we discovered that the turning point occurs when d = 0.500, which increases the average number of the neighbourhood (NH) from two to three neighbourhoods as shown in Figure 22 (c).

We also find that the number of points belonging to one neighbourhood or more neighbourhoods and the average number of neighbourhood members increase dramatically when the value of d increases. However, the number of points not belonging to any neighbourhood decreases incrementally with an increase in the d
Fig. 22 Variety of \( m \) value

value. This is because when the \( d \) value increases, it in turn, increases the likelihood of having more points of interest in the neighbourhood, as shown in Figure 23.

Fig. 23 Analysis for Melbourne City

Our study examines the correctness of result comparing the reverse nearest neighbourhood algorithm in two environments: road networks and Euclidean distance. We found that the number of neighbourhood members is much higher in Euclidean distance than in a road network, as shown in Figure 24. This is because obstacles such as lakes, buildings, parks etc. are not taken into account when processing the neighbourhood using Euclidean RNNH.
Also, we noted that for both the Euclidean distance and the road network algorithms, the number of neighbourhood members decreases dramatically with an increase in $m$. However, the number of neighbourhood members increases immediately, increasing the maximum distance between neighbourhood members ($d$) for the reverse nearest neighbourhood in both road networks and Euclidean distance. We find that the efficiency of the RNNH-RN query processing algorithm in road networks improves when the $d$ increase and the neighbourhood members on road networks are 9% fewer than for Euclidean RNNH.

5.4 High density Experiment

In this experiment, we use the dataset for a high-density environment that includes a variety of stores in the South-East Melbourne area comprising cafés, restaurants and groceries. We choose an area that has a large number of stores in order to test the solution in a high density environment. This enables us to test our algorithm’s feasibility and compare the results with the Euclidean RNNH algorithm in a high-density scenario.

The area size of the South-East dataset is $370 \text{ km}^2$, and contains around 1,865 stores. The graph for this dataset has around 195160 vertices and 215400 edges. The stores represent points of interest, 3% of which are supplier facilities. We conducted a geospatial analysis to describe and understand the RNNH-RN algorithm’s behaviour in a high-density environment.

We conduct a geospatial analysis study of the nearest point in the graph, and we calculate the network distance between each point of interest (POI) to the nearest neighbour. As shown in the graph, the maximum network distance to the nearest neighbour is 5.13 km, while the average network’s distance from one point to the nearest neighbour approximately is 100 m. We also calculate the total distance travelled to the nearest point in the graph; it required 181 km to traverse the whole graph to reach the nearest point. Most points are around 100 m from their nearest neighbour, while only a few points are above 5 km from the nearest neighbour. The results of the analysis for the nearest neighbours are given in Table
Table 6 Experimental Analysis for Nearest Neighbour South-East Melbourne

<table>
<thead>
<tr>
<th>Distance from</th>
<th>Number of shops</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-100 m</td>
<td>1458</td>
</tr>
<tr>
<td>100-200 m</td>
<td>208</td>
</tr>
<tr>
<td>200-300 m</td>
<td>61</td>
</tr>
<tr>
<td>300-400 m</td>
<td>29</td>
</tr>
<tr>
<td>400-800 m</td>
<td>44</td>
</tr>
<tr>
<td>800 m - 1 km</td>
<td>28</td>
</tr>
<tr>
<td>1-5 km</td>
<td>31</td>
</tr>
<tr>
<td>above 5 km</td>
<td>5</td>
</tr>
</tbody>
</table>

The maximum distance : 5.13 km
Average distance to nearest shop: 0.1021 km

We select one random query, the blue query as an example, from the dataset to study the outcome of the result of Reverse Nearest neighbour and Reverse Nearest Neighbourhood in Euclidean distance and road networks, as shown in Figure 25. As seen in Figure 25 (a) and Figure 25 (b), the results of reverse nearest neighbour (RNN) in Euclidean and road networks distance for selected queries are different, where it is clear that the outcome of the RNN in Euclidean distance involve more point in the result set than doses the road network distance. In Euclidean distance, it involves three points of interest that located on the right corner of Voronoi Diagram in the result of RNN while these three points belong to the facility of $f$ (red facility). This is because the Euclidean distance depends on the relative positions of the two points, while the distance on a road network depends on the relative positions as well as the road segments between the two points. Also, in this example, the outcome obtained by the Voronoi Diagram is different between the Euclidean distance and road network.

Consequently, the outcome of the reverse nearest neighbourhood query in Euclidean and road networks are different, as shown in Figure 25 (c) and Figure 25 (d). When the set has values of $d = 0.200 \text{ km}$ and $m = 4$, the Euclidean and road networks RNNH returns six neighbourhoods, which they have the same number of the neighbourhoods, but the neighbourhood members are different. The RNN in Euclidean involves more points than RNN road network distance does as shown in the strap neighbourhood that located the bottom of query points, there is two points of interest are involved in the result while road network distance result is not taken into account. Also, Figure 25 (c) illustrates the neighbourhood on the right-up side of query point has more neighbourhood members in the Euclidean distance than road network does as shown in Figure 25 (d), because these points in Euclidean distance are less than 0.200 km Euclidean distance. Conversely, in the road network, these points have more than 0.200 km of road distance.

In regard to the minimum number of neighbourhood members ($m$), we take facility $a$ as query point (the purple facility), Figure 26 shows the example. The
reverse nearest neighbourhood query on road network returns three neighbourhoods when the value of $m$ equals 2, while it returns only two neighbourhoods when $m = 6$. When the value of $m$ changes and increases from two neighbourhood members to six neighbourhood members at the minimum value, one neighbourhood is excluded based on the query preferences which is the left side of the query point. In Figure 26 (a), the minimum value of neighbourhood members is two, then the query returns three neighbourhoods. Figure 26 (b) shows the result when the minimum number of neighbourhood members is six. It returns only two neighbourhoods that have at least six neighbourhood members.

Figure 27 shows the results of varying the value of the maximum network distance ($d$). Figure 27 (a) depicts the RNNH query (purple query) example when $d = 100$ m. It is very clear that the same number of neighbourhoods is obtained for both queries even though the maximum network distances are different, as shown in Figure 27 (b). The same number of neighbourhoods are returned when the maximum network distance is 500 m. This is because in a high-density dataset, the points of interest are located very close to each other, so the neighbourhood
Also, we study the algorithm’s behaviour using different values of \(d\) and a static value for the minimum number of neighbourhood members \((m = 4)\). We study our proposed algorithm’s flexibility and note how many points are not mutually exclusive in a high density dataset. The red points are the points belonging to more than one query, the green points are the points belonging to only one query; the remaining grey points do not belong to any query. We see that the number of points of interest belong to only one neighbourhood and those in more than one neighbourhood remain stable even when the value of \(d\) increases by five times from 0.100 km to 0.500 km as depicted in Figure 28. This is because the query is distributed and located very close to the cluster of points of interest.

In addition, as the density increases, the number of queries required to obtain RNNH-RN increases as well as the value of \(d\) increases. We study the effect
of $d$ value on the efficiencies of RNNH-RN. This study illustrates the number of queries required to obtain RNNH-RN and the average number of neighbourhoods obtained by each query with different values of $d$. We conclude that the possibility of obtaining reverse nearest neighbourhoods increases dramatically when the maximum distance ($d$) between neighbourhood members increases. Second, we found that the number of neighbourhoods for each query declines with an increase in the maximum distance between neighbourhood members ($d$ value). When $d$ increases, so do the number of neighbourhood members, since they are combined together into one neighbourhood (NH). Figure 29 shows the results of varying the $d$ value.

Figure 30 illustrates the number of queries required to obtain RNNH-RN and the average number of neighbourhoods obtained by each query with different values for the minimum number of neighbourhood members ($m$). As we have seen when the value of the minimum number of neighbourhood members increases, the number of queries obtain neighbourhood (NH) and the average number of neighbourhoods decreases dramatically regardless of the environment. Also, we conclude that when the value of ($m$) increases, it reduces the likelihood of having more neighbourhoods. This excludes some neighbourhoods but does not satisfy the criterion regarding maximum network distance value ($d$).
Also, we find that the number of points belonging to one or more neighbourhoods and the average number of neighbourhood members increase dramatically when the maximum network distance between neighbourhood members (\(d\) value) is increased. Conversely, the number of points that do not belong to any neighbourhood decreases incrementally with increase in the maximum network distance (\(d\)). The reason is that, as shown in Figure 31, when the maximum distance (\(d\)) value increases, this increases the likelihood of having more points of interest in the neighbourhood.

We have compared Reverse Nearest Neighbourhood in road networks and Euclidean distance algorithm, as shown in Figure 32. We conclude that in the Euclidean Reverse Nearest Neighbourhood (RNNH) algorithm the number of neighbourhood members is much higher than for the Reverse Nearest Neighbourhood in road network (RNNH-RN) algorithm in all the three experiments. Also, in both algorithms, the number of neighbourhood members increases immediately, increasing in the maximum distance between neighbourhood members (\(d\)). Furthermore, it decreases dramatically with an increase in the minimum number of neighbourhood members (\(m\) value) in Euclidean and road networks. This is because when the maximum distance (\(d\)) increases, there is a greater chance of having more neighbourhood members, which leads to greater search distance and includes these members in the result set. We examine the accuracy of our proposed algorithm in road networks, and find that the neighbourhood members on road networks are 30\% fewer than for Euclidean RNNH as the road network reflects actual distances in all scenarios.
In this paper, we studied the problem of Reverse Nearest Neighbourhood in Road Networks. Reverse Nearest Neighbourhood in road networks (RNNH-RN) queries are motivated by our observation that Reverse Nearest Neighbour queries may not properly capture the notion of influence points. Hence, we introduced the concept of a Neighbourhood version of reverse nearest neighbour as a collection of chained points that are located along with road networks. Instead of fetching dispersed objects in the neighbourhood context as in Reverse Nearest Neighbour queries, we are interested in finding neighbourhoods of points. The neighbourhood

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**Fig. 31** Analysis for South-East Melbourne

**Fig. 32** Comparison RNNH and RNNH-RN algorithm for south-east Melbourne

**6 Conclusion**

In this paper, we studied the problem of Reverse Nearest Neighbourhood in Road Networks. Reverse Nearest Neighbourhood in road networks (RNNH-RN) queries are motivated by our observation that Reverse Nearest Neighbour queries may not properly capture the notion of influence points. Hence, we introduced the concept of a Neighbourhood version of reverse nearest neighbour as a collection of chained points that are located along with road networks. Instead of fetching dispersed objects in the neighbourhood context as in Reverse Nearest Neighbour queries, we are interested in finding neighbourhoods of points. The neighbourhood
finds a given query as their nearest facility among all the existing facilities, and
neighbourhood members within the same neighbourhood are geographically close
to each other. Our proposed approach is intended to find the most accessible
neighbourhood that considers the query as the nearest facility on road networks
while maintaining all its formal properties (not mutual exclusiveness). Extensive
experiments were conducted to present a thorough theoretical analysis of a spatial
network and demonstrate a viable solution for Reverse Nearest neighbourhood in
Road Networks queries, which is applies to different datasets’ densities.