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Research Article

Comparing Spatial Accessibility and Travel Time Prediction to Commercial Centres by Private and Public Transport: A Case Study of Oforikrom District

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The relevance of accessibility in shaping transport planning has often been neglected, hampering on decisions to improve transport efficiency. This is increasingly becoming problematic, as they often impede on economic and technological developments. Many studies on accessibility assert that it is easier for public transport to reach an activity centre than it is for private transport. For this reason, the research compares travel time forecast and accessibility levels with private and public transports en route to commercial centres. The research involves a 21-day transport survey for private cars and public shuttles in Oforikrom district using Global Positioning System (GPS) probe to record the traffic performance indicators to be analyzed in a GIS environment. The results of the study display on a map the level of accessibility via the modes, and a comparative line plot of travel time with private and public transport. The study reveals that private cars in the district generally perform better than public shuttles on the level of accessibility, and travel time. The execution of the research shows that the convergence of choice of transport mode and travel time dynamics is crucial for policymakers to implement diverse transport modes and commuters to choose a mode that has low accessibility cost.

1. Introduction

Continuous population growth and landuse drive the need to explore the cost to access a specific set of services or commercial [1–3]. The community of planning and transport practitioners agree that the fundamental concept for examining human participation in activities in the urban environment is accessibility [4]. The concept helps to measure and highlight, in time and space the travelling distance along a road [5, 6]. It can derive insight into the performance of transport modes, zones and individuals [5, 7, 8]. Many studies on accessibility assert that is easier for public transport to reach an activity centre than it is for private transport. This may be far from reality for all road network locations since it prompts a research question of which transport mode is faster to travel with. For this reason, the study described in this paper compares travel time forecast, and accessibility levels with private and public transports en route to commercial centres.

The methods for evaluating accessibility levels and forecasting travel time to commercial centres are implemented, and their various outcomes are declared. The approaches to measuring the distinct transport modes are applied in the form of a case study to the district of Oforikrom in Kumasi, Ghana. Therefore, the article shows the level of accessibility and travel time forecasting with the modes of transport in the district.

Our motivation to study this issue springs from the experience in accessing activity centres by private and public transport, particularly in Kumasi. This modern research method is rarely applied in Ghana for transport planning. Therefore, the results of the present study is to inform policymakers on the direct impact of distinct transport modes on accessibility, hence the need for diverse transport modes. This is important as it is one of the key characteristics of improving socio-economic and technological developments [2, 9].

The remainder of the paper is organized as follows. After the introductory section, the next section presents a theoretical framework on technical indicators and the adopted methods used to measure cost on accessing activity centres. The next section describes the study area and the modelling procedures of the paper-based on potential accessibility and KNN Regression. The next part presents on a map the estimated results on accessibility levels with private and public transport modes. Furthermore, the section compares the travel time prediction for both transport modes. Finally, the last section conclude our study.

2. Accessibility to Commercial Centres

2.1. Travel Survey from GPS Technology. Global Positioning System (GPS) are used in many applications such as urban developments, agriculture, social sciences, etc. [10]. The system uses satellite information to provide positioning, navigation, and time via GPS receiver. Many devices such as cellphones come with GPS embedded in them, which makes location data like transport survey data easier to collect [9, 11, 12]. This has been alternative for Automatic Vehicle Location (AVL) since it offers cost-effective means of collecting a large amount of transport data [13]. In October 1993, Maricopa Association of Governments conducted travel speed and delay studies, and concluded that "*GPS technology provides a novel approach to collecting network travel speed for processing*". Moreover, Tong et al. [14] investigated on "*Traffic information deriving using GPS probe vehicle data integrated with GIS,*" and concluded that *"GPS probe vehicle data may be an alternative method for traffic data collection in some areas*". Several authors have agreed that there is no single right way of measuring accessibility [14], so this permits realistic proxies regarding the situation at hand. The GPS device is used to measure relative barriers that impede travel time on route networks in terms of cost, reliability and effectiveness. The barriers recorded on the route network are topography, stops, turns, travel speed, potential demand and travel time. These barriers are based on the assumptions as shown in Table 1 as measures to illustrate better accessibility in the district.

2.2. Geo-Information Technology and GPS Travel Survey Data. The integration of geo-information technology with GPS has become a standard application in transport planning and landuse modelling [3, 10, 15]. Maps are a popular product for geo-information technologies. These maps play a key role in enriching people's understanding of existing and planned developments, routing and logistics, accessibility provided by transport routes, etc. [9, 16]. The key components in the technology for transport application are encoding, management, analysis and reporting [4]. This technology is useful in the study as it offers visualization tied to a geographic location and informs people on-trend and relationships embedded in a dataset.

2.3. Accessibility and Travel Time Prediction. Accessibility as a direct expression of mobility can be connected to an array of economic and social opportunities. Efficient transport systems offer a high level of accessibility, while less developed ones have lower accessibility. The challenges associated with accessibility can be assessed using nodes and links. The measurement exhibits the general ease of accessing opportunities [18]. Geo-information technology has improved the standards of data files that are used in transport planning and modelling, by enabling the use of better data. Accessibility measurement technique uses the rows and columns in a transport matrix, which is equal to nodes and links in a network. These techniques are Geographic and Potential Accessibility [4]. This paper adapts potential accessibility since it considers the summation of attributes based on the assertion that all locations are not equal. The most accessible can be assessed using the equation below.

Table 1: Barriers as indicators modelling accessibility.

Indicators	Assumptions
Topography (flat = 0, steep = 1)	If land topography is steep, there will be physical impediments to transport
Stops (min/km)	If stop time is high, then movement ceases most times or movement is slow
Turns (min/km)	The higher the turn time, the difficulty to change direction to destination
Travel speed (km/h)	The higher the travel speed, the easier it is to access activity centres
Potential demand (number of people/km)	If demand is high, there is delay in moving people to activity centres
Travel time (min/km)	If travel time is high, movement is faster and it is easier to access activity centres

$$A(P) = \sum_{i=1}^{n} P_i + \sum_{i=1}^{n} \frac{P_j}{d_{ij}}, \tag{1}$$

where $A(P)$ = Potential accessibility matrix, d_{ij} = distance between location i and location j , P_j = attributes of place j, such as its population, retailing surface, potential demand, parking space, etc. n = number of locations.

Travel time estimation is important to the development of transport planning, designing and operations [18, 19]. This requires statistical learning technique to estimate the dynamics in travel time using time-dependent delays. The time-varying observation is a key feature in developing the model. The adapted model used in the estimation is called KNN Regression. The transport survey data is first trained and later deployed to predict new data or future data after the model test is satisfying. The method in KNN is

$$M_K = \frac{\sum_{i=1}^{n} 1/(distance)^2 * ti}{\sum_{i=1}^{n} 1/(distance)^2}, \tag{2}$$

where M_K = the query of prediction k, i iterates over the nearest neighbours to n in the dataset, and ti is the value of the target of a feature.

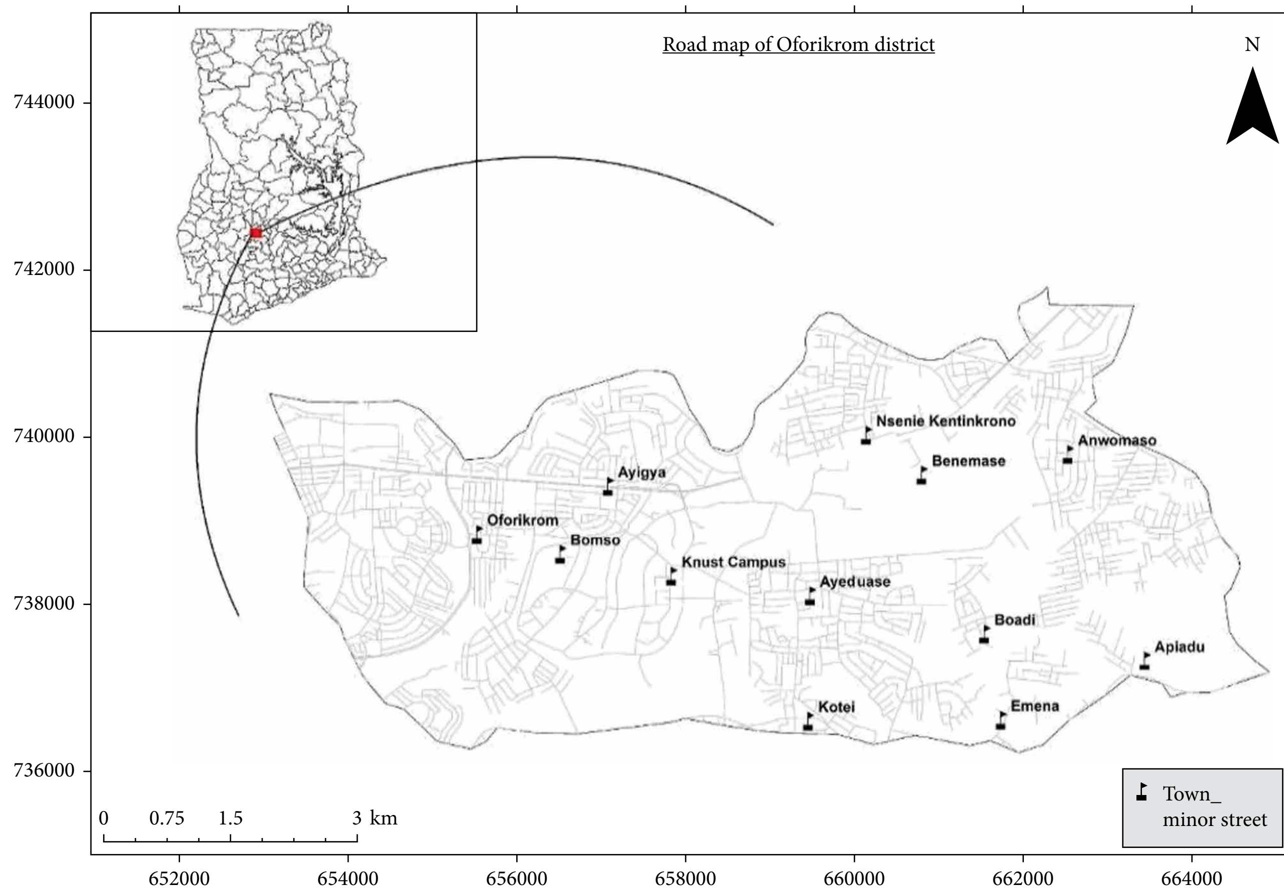

Figure 1: A map of Oforikrom district.

A community has potential economic growth if activities in the area are highly accessible, and these opportunities can be assessed using accessibility concept. The concept is a sensitive assessment encoded in GIS with GPS technology, which directly informs about "winners" and "losers" in a given scenario; indicating levels of accessibility with distinct transport modes. Furthermore, travel time prediction is important information for travellers to make decisions, therefore, the dynamics of travel time stipulates a statistical learning technique to estimate travel.

3. Case Study

Oforikrom district is located at the southern part of Ghana, and part of Kumasi metropolitan area (KMA) as shown in Figure 1. The district comprises of Appiadu, Kotei, Ayigya, Ahenbronum, Aketego, Bomso, Anloga, Tech, Oforikrom, Anwomaso, and its geographical location falls between 6°41′19″N, 1°36′19″W, and 6°40′46″N, 1°30′42″W. Across the district, the three main commercial centres can be located at Tech junction, Knust commercial area and Mckeon. Wholesale and retail, repair of cars and motorcycles are very notable in the area. In manufacturing, they have small scale industries in the field of leather works, furniture works and fashion design. Accessing these activity centres requires the use of private car or public shuttle (Trotro) which are the popular transport modes in the district.

4. Research Method

The method of forecasting travel time and modelling accessibility of transport modes consist of several sequential steps. A reconnaissance for towns and routes in Oforikrom district were conducted as a first phase of the project. This was a basic requirement for recording travel data since the survey needs to be accurately tied to a specific geographic location. This was achieved using a mobile embedded GPS to record location points of turns, traffic lights, towns, and activity trips of origin (terminals) and destinations (commercial centres) on the route network. The recorded locations were later integrated into Google earth application and ArcGIS to generate a digital map in Figure 2.

The map on sheet combined with GPS was used to manually record the traffic performance of physical attributes on each segment of the road. These attributes include travel speed, travel time, stops, turns and potential demand. The data were collected for both public shuttles (Trotro) and private cars from morning (7–9 AM) and evening (4–6 PM) during their peak periods. An average speed of the vehicle to the destination is recorded on the GPS for each segment and is copied on a clipboard. The stopwatch in GPS records travel time, and includes segmented time for delays on stops and turns. The potential demand for the transport mode was also recorded at each segment, and all the data were copied on the clipboard. The sample of the recorded attributes for both private and

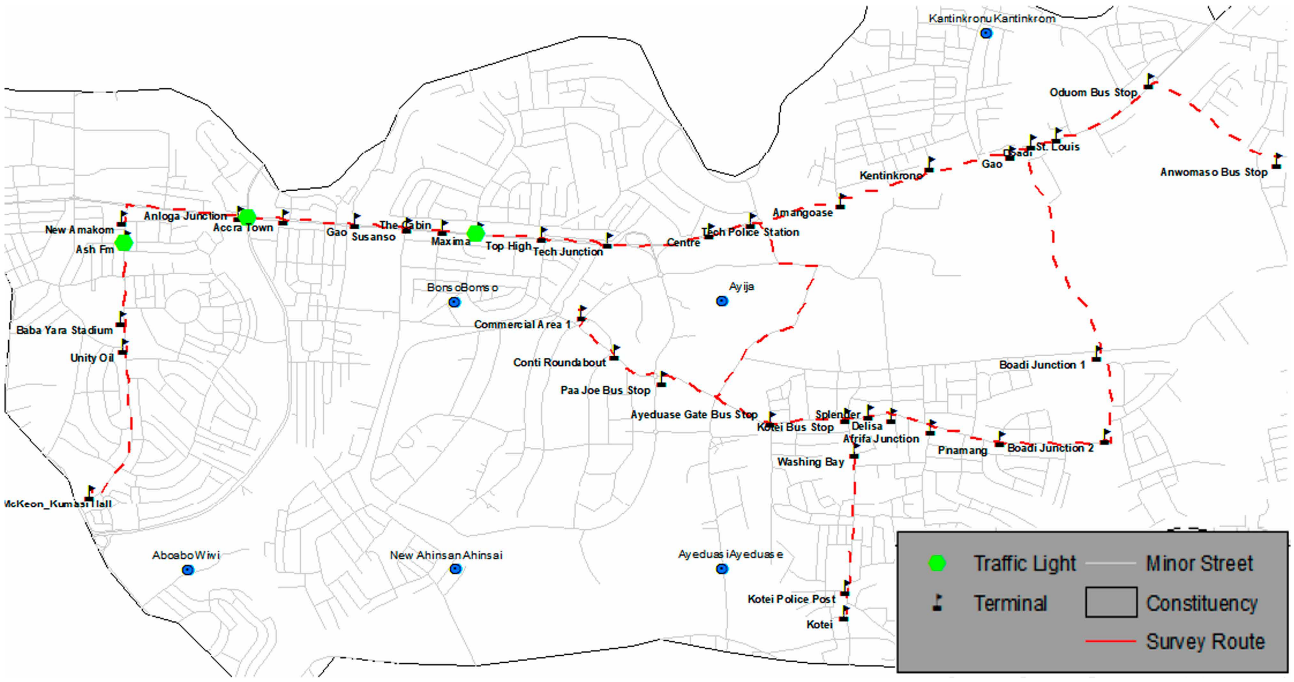

Figure 2: The map of survey route to recording physical attributes at each segment.

public cars was 858. The data recording for morning and evening were averaged, and the maximum was used.

4.1. Modelling Accessibility. In assessing different transport modes and their access to commercial centres, the potential accessibility method sums the cost to travel by car or public transport from location i (origin) to location j (destination) [4, 5]. The first phase of the technique was to build an origin to destination (O-D) cost matrix of distance for the transport network. This matrix in pairwise comparison added the shortest distance from an origin to commercial centres.

The second phase was to calculate the total sum of recorded physical attributes on each segment for private cars,

$$A = \sum_{i=1}^{n} P_i, \tag{3}$$

where P = speed, travel time, slope, potential demand, and slope. The resulting sum was used to divide each corresponding total distance in the graph matrix,

$$\sum_{i=1}^{n} \frac{P_i}{d_{ij}}. \tag{4}$$

The values on each row were then added, and the results show the level of accessibility. The maximum values indicate high accessibility. This was undertaken separately for private cars and then repeated for public transports.

4.1.1. The Level of Accessibility with Different Transport Modes in a GIS Environment. The acquired values of accessibility for private cars and public shuttles were joined with a node layer in ArcGIS 10.5. They both had similar ID to join the database. The natural neighbour interpolator tool in Arcmap was run using the obtained results for accessibility as the z dimension. This process produced a surface that showed levels of accessibility for the extent of the route network. A point data as commercial centres in the district were used as query points to show the ease to reach the location by either private cars or public shuttles.

Finally, the Thiessen polygon tool was also run for the nodes to show near segments and their bounding level of accessibility. This showed the level of accessibility for each segment in the network considering private or public transport.

4.2. Predict Travel Time. To determine the future cost of travel time on the route, average speeds, maximum stops and average travel times collected from the segments in 21 days ($N = 21$) were used. The data was exported to a text file, and "open" command in python was used to get data. Before training the regression model, preprocessing the data was necessary. First, data normalization was implemented by using the minimum and maximum of the entire dataset as shown in Equation (5). This was necessary as different features had different measurement scales which may have an effect determining the results. For instance,

$$\text{Average speed: } \frac{43.00 - \min}{\max - \min}. \tag{5}$$

Secondly, average speeds, maximum stops, and average travel time were plotted in feature space. This was to inform if the data was linearly or nonlinearly separable and, which distance method to adapt. Notwithstanding the separation type, KNN could separate the data and the euclidean method was adapted. Next, was the average travel speed and maximum stops were split as features for the model while average travel time as a target feature.

Table 2: Travel survey data for private cars on mondays in all the weeks.

Centre names	Average speed (AM)	Average speed (PM)	Average travel time (AM)	Average travel time (PM)	Average stops (AM)	Average stops (PM)	Average turns (AM)	Average turns (PM)	Average potential demand
Tech junction	32.16	41.19	3.26	1.13	0.00	0.00	0	0	0.00
Top high	33.01	40.38	0.78	0.13	0.00	0.00	0	0	0.00
Maxima	41.59	44.93	0.12	0.17	0.00	0.00	0	0	0.00
The cabin	42.63	37.36	0.14	0.23	0.00	0.00	0	0	0.00
Susanso	49.34	33.46	0.29	0.84	0.00	0.00	0	0	0.00
Gao	42.67	28.61	0.39	0.33	0.00	0.00	0	0	0.00
Accra town	44.04	26.63	1.44	1.78	0.00	0.00	0	0	0.00
Anloga junction	35.49	24.88	1.16	5.01	0.00	0.00	0	0	0.00

Table 3: Travel survey data for public shuttles on mondays in all the weeks.

Centre name	Average speed (AM)	Average speed (PM)	Average travel time (AM)	Average travel time (PM)	Average stops (AM)	Average stops (PM)	Average turns (AM)	Average turns (PM)	Average potential demand
Tech junction	29.49	41.19	4.92	1.13	1.67	3.67	0.00	0.00	27
Top high	33.01	40.38	0.78	0.13	0.00	0.00	0.00	0.00	6
Maxima	41.59	43.93	0.12	0.23	0.03	0.00	0.00	0.00	3
The cabin	42.63	37.36	0.14	0.23	0.00	0.00	0.00	0.00	1
Susanso	49.34	33.46	0.29	0.84	0.00	0.00	0.00	0.00	4
Gao	42.67	28.61	0.39	0.33	0.00	0.00	0.00	0.00	0
Accra town	44.04	26.63	1.44	1.78	0.00	0.00	0.00	0.00	5
Anloga junction	35.49	24.88	1.16	5.01	0.33	0.67	0.00	0.00	19

The similarity-based prediction model used euclidean distance as weight, and 3 neighbours to predict travel time as shown in Equation (2). In selecting K^{th} neighbours, a range of numbers as neighbours was plotted against their mean of absolute deviation. This was to help select the minimum absolute deviation error and Kth neighbour which is optimum. Afterwards, the data were fitted inside the model by splitting into two, with 80 per cent going into training, and 20 per cent for testing. The model could predict new data by calculating the euclidean distance between the queried points and feature dataset. It then commits into memory the first three closest distances to strike average as shown in Equation (6) below.

$$M_{[<0.066,\,1.000>]} = \frac{5.067 + 3.012 + 0.188}{3}. \tag{6}$$

The model was validated by predicting existing data to see its efficiency. It was then tested with new data to predict travel time.

5. Results and Discussion

The results of modelled accessibility and travel time forecasting are described in Sections 5.1 and 5.2.

5.1. Assessing Accessibility to Commercial Centres with Car and Public Transports. Tables 2 and 3 shows data recorded on each segment for private and public cars to model accessibility and travel time forecasts.

Demand for public shuttles is more than that of private cars shown in Tables 2 and 3. Most private cars drive straight to destinations with fewer activities or stops; while public shuttles often make stops to pick new passengers.

The ease with which private cars reach commercial centres was assessed and compared to public shuttles in Figures 3 and 4. This outcome is essential in the link between demand and supply in Sustainable Development Goals (SDG) 8 to mitigate the high cost for transport modes operating in the district.

It is salient to commuters as relative transport cost influences the costs of commodities as well. The results show low accessibility at Tech junction by private cars and public shuttle. This informs on the difficulty to reach the location due to the high cost of speed, travel time, potential demand and number of stops. Furthermore, it indicates average accessibility at KNUST commercial area for both transport modes, and high accessibility at Kumasi Mall with private cars and public shuttle with low travel cost. The polygon defines the level of accessibility for each segment throughout the network. The level of accessibility with private cars and public shuttles in the district highlights the need for diverse transport modes like trains, bicycle routes, walkways. The drawback with the accessibility method is that not all impact indicators such as brakes, fuel cost, etc., were considered.

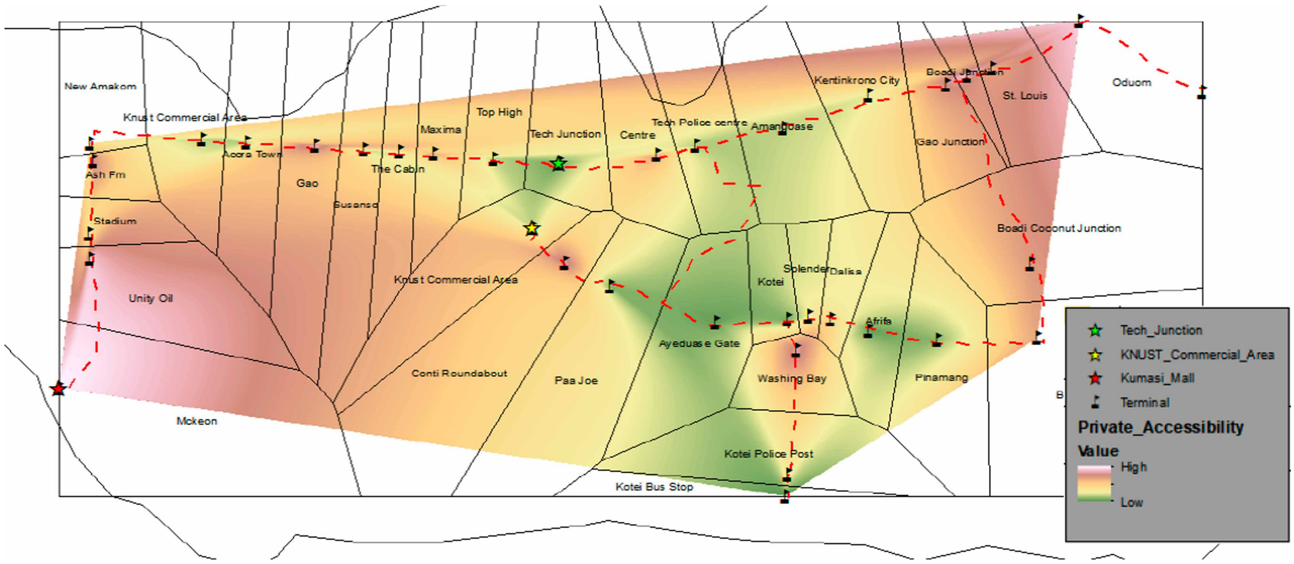

FIGURE 3: Accessibility level to commercial centre by private cars transport with green as low accessibility, pale yellow as average accessibility and brown as high accessibility.

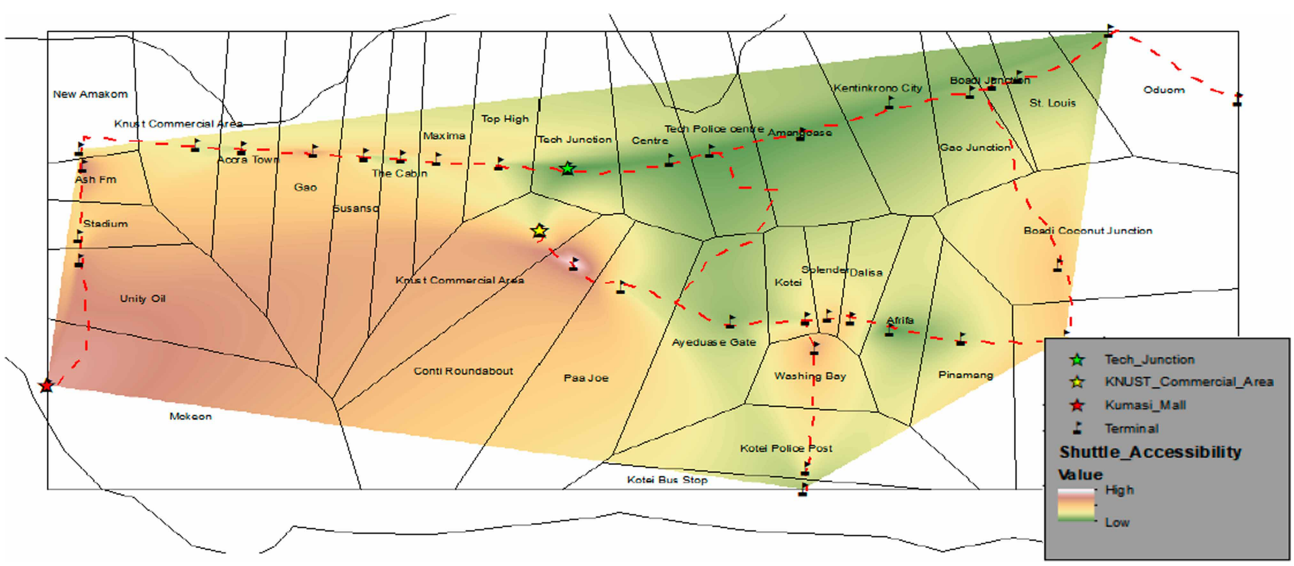

FIGURE 4: Accessibility level to commercial centres by public transport with green as low accessibility, pale yellow as average accessibility and brown as high accessibility.

Generally, private cars have the most accessible locations compared to public shuttles.

5.2. Travel Time Prediction. Considering the sensitivity of the predictive model, mean absolute deviation for the test data showed $k = 3$ as an optimum number of neighbours as shown in Figure 5. This is important to represent delays on the network and how it can be addressed to increase productivity in the district. Ghana Highway Authority and commuters are keen in knowing the future cost or penalty in reaching a destination.

The model was validated by predicting the travel time from Pinamang to Paa Joe showing an average error of about 10 minutes in Figure 6.

Travel time estimation for the private car was compared against public shuttle from Oduom to Tech Junction, and Emena to Tech Junction in Figure 7. This is important information as it may guide the individuals to reach a location in time [19]. Considering time-dependent delays, KNN regression technique can separate both linearly and nonlinearly separable features.

6. Conclusions

Forecasting travel time combined with performance modelling of accessibility, with private and public cars in Oforikrom district, yields a result that respond to the faster mode to travel

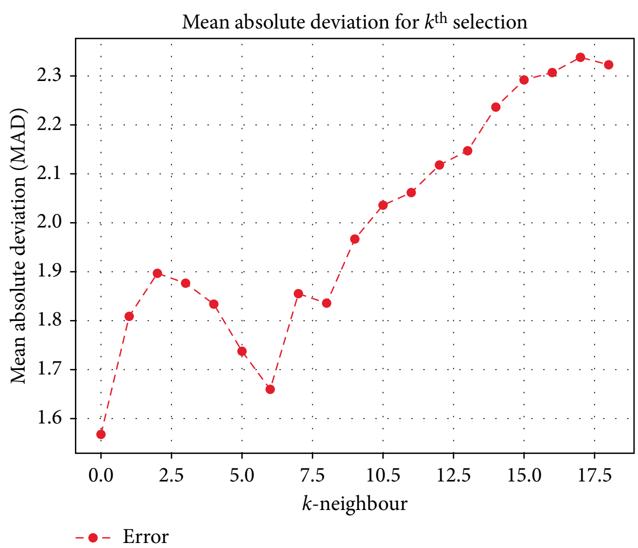

Figure 5: Choosing optimum k-neighbour for the model. The selected neighbour was 3.

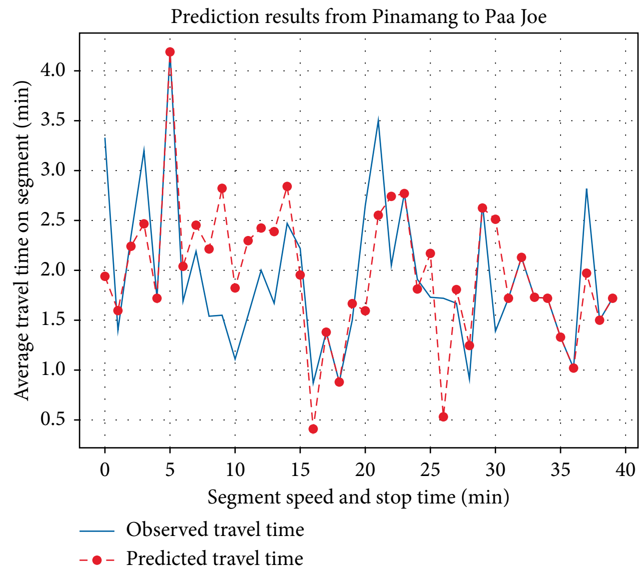

Figure 6: Predicting test data using $k = 3$ and $N = 21$.

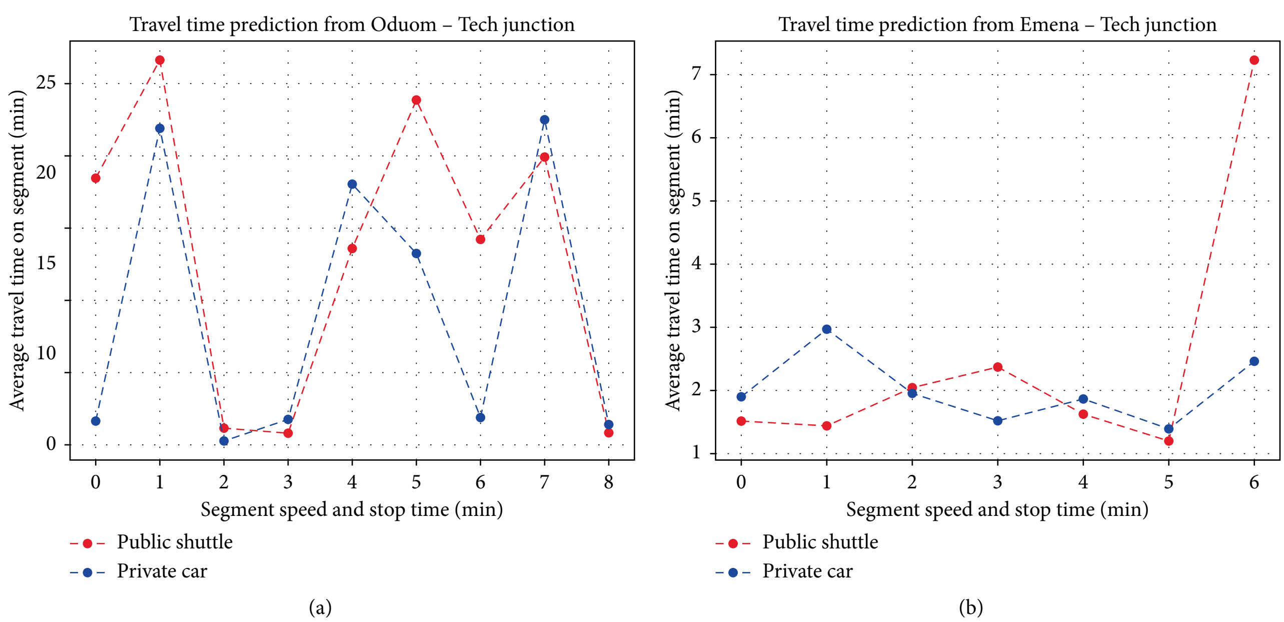

Figure 7: Travel time estimate from (a) Anloga junction to Mckeon, and (b) Oduom to Tech junction for private and public transport.

with. The study aims to inform policymakers on the impact of distinct modes in accessibility. To achieve the objective, the study started with modelling accessibility by private cars and public shuttles to commercial centres in the district. An accessibility measure integrated with natural neighbours and voronoi (Thiessen polygons) in the GIS environment communicate easily by showing low, medium, and high accessible locations. Modelling data were collected during the peak period from morning and evening, and the sample size was 858 in 36 route segments. Travel time forecast to destinations was compared for modes as penalties or delay. The time cost of each mode was calculated using the k-nearest neighbour regression. The model on query with stop time and average speed on the segment informs the average time of travel to destination. The analysis of the study confirms that the commercial centres in Oforikrom district are highly private cars- accessible areas, than public shuttles. The study also reiterates the fact that private cars generally perform better than public shuttles in the area. The study indicators permit comparison of relative modes to key destination areas. The analysis is relevant in the context of continuous landuse and population growth ensuring that planning policies are developed to mitigate transport cost and stress on transport modes, thus limiting congestion. This combined approach can be extended and used for further research in other transport locations to inform on the effect of diverse modes on accessibility.

Data Availability

The data for the research can be accessed from google drive using the link https://drive.google.com/file/d/1oB-JBQS3_9b49AA3Q0vuYvAtijnDgrhn/view?usp=sharing.

Conflicts of Interest

There authors declare that there are no conflicts of interest regarding the publication of the paper.

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