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Multi-Criteria A* Route Recommendation for Intelligent Urban Mobility: Design and Evaluation of a Port Harcourt Traffic Advisory Application

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Abstract: Considering several factors is necessary to find the ideal route in a busy urban area. For example, the quickest route may not be the most fuel efficient or the safest in an everchanging traffic situation. This research examines a route recommendation component in the context of the Intelligent Traffic Advisory Model (ITAM) for Port Harcourt Metropolis, Nigeria. The source thesis describes the system as evaluating possible routes based on predicted travel times, congestion, distance, fuel consumption, and hazards. For the shorter-distance route, Dijkstra's algorithm is used; for the route with less 'remaining' travel time, A* search is used. The component is reported to integrate various elements, including a web front-end, mapping services, a route recommendation system, a database, and a python-based route planner. A trip from Garrison to Eleme Junction was used to analyze Aba Road (an estimated journey time of 40 minutes), Station Road via Airforce (35 minutes), and Trans Amadi - Elelenwa (45 minutes). Based on this analysis, the system endorsed Station Road. The average response time for the system was reported as 3.15 seconds and user ratings (4.3/5, from 500 users) indicated a high level of satisfaction. Other reported outcomes of the use of the system included average commuting time reductions of up to 18.4%, and a peak hour traffic throughput improvement of 22.1% and approximately 12.9% improvement in fuel efficiency. Because documentation of the evidence provided in the thesis is scant, the findings reported above (and contained in the findings section of the thesis) require validation and extensive peer-reviewed evidence for wide spread acceptance and generalization. Based on the above, this paper describes the multi-criteria routing methodology, analyzes possible limitations, and offers more rigorous assessment as part of a recommendation for future publication and deployment

Keywords: A* search; Dijkstra algorithm; route recommendation; intelligent transportation systems; traffic advisory; multi-criteria optimization; Port Harcourt.

I. INTRODUCTION

Urban commuters make choices about routes with some degree of uncertainty. Distance alone is usually an inadequate criterion for route choice. A shorter route can become congested or blocked because of an incident or road works. A longer route may be less congested and, therefore, have better and more reliable flow. Commuters have different levels of concern for factors like fuel consumption and consumption, safety, and comfort. An intelligent system for route advice must have a representation of a road network, and integrate traffic information and a procedure for ranking the alternatives.

The focus of this paper is on the development of an Intelligent Traffic Advisory Model to enhance urban mobility. The model describes the limitations of the reactive management of traffic and offers a route recommender that utilizes the user's origin and destination, determines candidate routes, and evaluates the routes using a variety of criteria such as travel time, congestion, distance, fuel consumption, and safety, including hazards and construction. Dijkstra's algorithm is used for determining the shortest path. A* search uses the actual path cost and, in combination with a heuristic estimate, determines the remaining cost to the goal.

Routes with the lowest cost may not be the shortest. The increasing congestion in the road network increases the travel time uncertainty and imposes costs on the users of the road, including commuters, freight operators, and users of public transport and emergency services.

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Active traffic management systems provide timely and relevant information to users and help users respond to changing conditions along the system. The effectiveness of these systems, however, depends on the quality and timeliness of the information. It also depends on how route recommendations impact network traffic flow (Afrin and Yodo, 2020; Cheng et al., 2020).

Systems to recommend routes should not be evaluated by the presence or absence of a recommended path. The evaluation should include quality of prediction, times to compute a prediction, user trust, how the system handles changing weather, and if recommended detours improve system performance as opposed to simply moving congestion to other paths.

This paper separates the multi-criteria routing component from the more extensive ITAM system. It describes components of the route-cost model, the role of A* and Dijkstra, the context of the implementation, the results of the work described in the thesis, and the choices the authors made to support a thorough evaluation.

A. Research Problem

In this chapter, we assess a component of the intelligent traffic advisory system. The component uses A* pathfinding, which extends Dijkstra's algorithm, to recommend multi-criteria routes to users. The extension accounts for traffic conditions. We examine variability in travel conditions and time as factors that complicate route recommendation. When using different measures of analysis, the path with the shortest distance might not be the path with the lowest travel time or fuel consumption, or the path with the least exposure to road hazards. This means that to provide the best traffic advisory system to the users, the complete road network and the time varying cost of travel need to be taken into consideration.

B. Aim and Objectives

This paper aims to review the multi-criteria route recommendation component based on A*-algorithm integrated in the intelligent traffic advisory system, focusing on Port Harcourt, Nigeria. This review aims to accomplish the following: (a) identify criteria for assessing alternative routes; (b) explore Dijkstra's algorithm and A* as a traffic-aware search method; (c) appraise system architecture and information flow; (d) illustrate routes and present performance metrics of the system; (e) analyze the available evidence within the limits of the stated objectives; and (f) propose a replicable and benchmarking framework to test the system.

C. Contribution

The paper describes a structured way to evaluate routes in an urban traffic advisory system. It describes the difference between recommendations based on shortest-distance pathfinding and route-based traffic-sensitive pathfinding and evaluates results presented in the thesis. The paper presents a validation framework to assess algorithmic accuracy, prediction, and operation of the system as well as impacts on system mobility in an urban setting.

II. RELATED LITERATURE

A. Intelligent Traffic Advisory Systems

A key feature of intelligent transport systems (ITS) is the integration of access to the constantly updating traffic information, advanced route-search algorithms, and traffic advisory systems. Timely collected traffic data must be processed and addressed inconsistencies. Costs must be calculated for different routes and recommendations provided in an easily comprehensible format. The functions of ITS include: traffic surveillance, data and information integration, and route optimization. It is evident that traffic advisory systems are as a result of the integration of these functions (Lima et al., 2017; Behrooz & Hayeri, 2022).

This research reviews a variety of current traffic technologies, such as GPS, camera-based, IoT, and graph based forecasting, as well as machine learning. Some of these technologies can certainly aid route advisory systems; however, there are a number of constraints. Traffic cameras, for example, can malfunction in inclement weather. Sensor networks require a sufficient communications and infrastructure support and maintenance framework. GPS data can become sparse and less reflective of current conditions and situations with the passage of time, for example due to the modification or reconstruction of roadways. A reliable system should therefore capture and save the information about the data sources and the times at which the data was captured, and provide an alternative when real-time information is not available.

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B. Shortest-Path Algorithms

Dijkstra's algorithm works for non-negative edge weights to determine the shortest paths from a starting node. This algorithm can be used to find the path with the lowest total distance or the quickest path with the least time estimates, respectively, with distance and travel time, respectively, representing edge costs. However, the algorithm does not predict how the travel-time estimates will change. It depends on the costs assigned to the edges in the network. Thus, in general, the meaning of the shortest path depends on the optimization criteria, which can be either distance, travel time, or some other weighted costs.

For A* search, the cost of moving from the starting point to a particular node is added to the cost of moving to the node from the previous node, which is represented by the function . The remaining cost to the destination, is represented by the function , and is estimated by a heuristic. If the heuristic is admissible, i.e. it never overestimates the actual remaining cost, A* search can find the optimal path with respect to the cost function under the relevant conditions. For road networks, the heuristic can be straight-line distance if the optimization criterion is distance, and lower-bounded travel time if the optimization criterion is travel time. Because distance and travel time are measured in different units, using distance as a heuristic for travel time can give wrong results.

Using heuristics doesn't necessarily mean that A* automatically provides better routing solutions than Dijkstra. The structure of the network, the cost function, heuristics, and the approach to process and update travel time estimates also play an important role. From a theoretical standpoint, both algorithms can find the same optimal solution. A* may evaluate fewer nodes than Dijkstra, especially if the heuristic is meaningful and guides the search in the right direction. Integrating travel time estimates with varying levels of sophistication adds to the complexity of the problem. From a routing perspective, a trade-off has to be made: be it operating with a constant estimate of travel time, refreshing route costs periodically, or limiting recalculation of routes to when a significant cost saving is expected.

C. Multi-Criteria Route Evaluation

The source thesis identifies five main areas for comparing routes: travel time, congestion, distance, fuel consumption and potential penalties for violating road rules for hazards and/or construction. This presents a clear case of multiple, conflicting objectives. For instance, the route with the least travel time may cover a greater distance than the route with the higher congestion, and a fuel efficient route may take longer. Trade-offs like these may be captured via a combined cost function or by applying the Pareto principle to explicitly express the compromises made between objectives.

One of the ways to capture the total cost of a journey may be through a normalized weighted function as below

$$C(r,t) = w_TT(r,t) + w_CC_g(r,t) + w_DD(r) + w_FF(r,t) + w_HH(r,t)$$

Here, is travel time, is congestion, indicates distance, refers to fuel consumption and accounts for hazards and construction penalties, respectively.

The weights of the criteria determine their relative importance, and, after normalization, they should add up to one. Differences in scale of various criteria must be removed. Consequently, the numerical values of the criteria will not make one criterion overly dominant. Weight values can be determined in a stakeholder meeting, from user preferences, or from policy rules. The thesis refers to user preferences. However, the materials reviewed did not provide sufficient information to develop a validated set of weights. Therefore, the equation shows the formalism of the proposed design, as opposed to representing parameters of the actual implemented system.

A better design would treat some criteria as hard constraints while others would allow a trade-off. Prohibitive criteria, such as closed roads or specified turns, as well as unsafe conditions, should be considered as hard constraints. Other considerations, such as congestion or travel time, should be considered as penalties. A closed road should be removed from the candidate network, or if it is not removed, a high penalty should be assigned to it. A low penalty would not be appropriate because the algorithm might select that road if the other candidate roads have higher computed costs.

D. Research Gap

The management of traffic has been approached by research in a number of ways, including dynamic traffic forecasting, traffic flow representation as a directed graph, selecting optimal routes, and adaptive traffic control. The thesis notes that some approaches struggle with scalability, dependence on specialized equipment, or simplistic treatment of challenges that occur in real-world road networks. This work aims to integrate locally-relevant traffic indicators in a practical route-ranking framework, and assess the system from an algorithmic and user-experience

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perspective. The work is novel in the integration of A* or Dijkstra's algorithms in a traffic advisory system, and in describing the rationale and some of the challenges of its development.

III. METHODOLOGY

A. Research Approach

The research employs design science to create and validate an ITAM artefact using a design science approach. The development process includes identifying the problem, establishing objectives, designing and constructing the system, demonstrating its functionality, assessing its performance and providing evidence of results. This approach is applicable to information systems research because it combines a computational artifact with evidence of its performance (Geerts, 2011).

The study focuses on Port Harcourt Metropolis. According to the study, field surveys helped to ascertain the location of traffic congestion hot spots. Other variables assessed include traffic volume, weather, and historic traffic data. The thesis also cites several limitations including real-time data constraints, inconsistency in data quality and completeness, technology resource constraints, and insufficient model validation. These must be taken into consideration when evaluating the reported performance of the system.

B. System Architecture

The process of system recommendation involves identifying a starting and ending point. Once this is done, the system determines all possible paths between the two end points. Next, the data layer determines the current and historic condition of the segments along the paths, as well as threats along the paths. Road segments are assigned costs based on evaluation criteria chosen by the commuter. Using the costs and the remaining end points along the paths, Dijkstra's algorithm or A* searches for the least costly or best way, respectively. Finally, the endpoint and time to arrival is determined along with other recommendations.

The technology included in the implementation consists of but is not limited to Python, machine learning, mapping, visualization, Flask, Zookeeper, Kafka and various databases. Different parts of the manuscript suggest different interfaces and database technologies. Prior to publication, it is recommended the authors review the documentation of the deployed application to resolve the discrepancies described and focus on the actual technologies deployed rather than speculate based on ambiguous descriptions. Thus, this paper focuses primarily on the architecture of the deployment, avoiding any speculation based on unsubstantiated claims.

C. Cost Function and Data Handling

Let's define the generalized cost of each directed road segment as follows:

$c_e(t) = \alpha\tau_e(t) + \beta\kappa_e(t) + \gamma d_e + \delta\varphi_e(t) + \lambda\rho_e(t)$

These are the estimated travel times, congestion, distance, fuel consumption, and road hazards and/or work. Coefficients α, β, δ, and λ indicate user preferences or policy priorities. All the variables described must be in the same unit in order to be combined. If trade-offs are defined in the application, e.g. "fastest route" vs "shortest route", the weights can be defined in a way to allow the user to control it and understand the consequences of each. When trade-offs are not defined, i.e. the user selects the default, it must be clear to the user what the consequences of the default selection are.

Traffic records should include timestamps and ratings that reflect the confidence level of the data. The absence of live traffic data should not be assumed to mean that conditions are free-flow. The system should be able to combine recent observations with historical traffic data, and express an estimate as an opinion, e.g. "Driving conditions are probably congested." If multiple data sources give conflicting information, a data fusion strategy should be employed. Alternatively, the system should assign greater weight to the data source with the better track record. These are vital because route search algorithms, in an attempt to optimize costs, can amplify or exacerbate systematic errors in the data supplied to them.

D. Dijkstra Baseline and A Search*

Dijkstra's algorithm is used to compute shortest-path trees in directed graphs where edge costs are non-negative. To compute the shortest path from node to all other nodes in the graph, starts with node , and initializes the distance of node to zero and to infinity for all other nodes. The algorithm then selects the unsettled node with the least distance, and updates the distance of its adjacent nodes via relaxation. This is repeated until node is settled, or all nodes have been relaxed.

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A* search relies on the evaluation function to choose which nodes to prioritize. The function incorporates the generalized cost, g(n), from the origin to a particular node n and the estimated remaining cost, h(n), to the destination. Travel time being the optimization criteria implies that an appropriate heuristic can be defined as the straight line distance divided by an upper bound of the speed limit. Therefore a lower bound of the remaining time can be established. If the cost function is made up of multiple components, then the heuristic should also be made up of the multiple components to ensure the minimum remaining cost is not overestimated.

The routing engine should take into account changes in road conditions. The routing engine may require recalculation with new incidents, road closures, or significantly longer travel times on alternative routes. To prevent unnecessary and repeated changes to recommendations, a threshold or penalty may be applied to route switching. Based on this threshold or penalty, the advice may remain the same or change to a different route.

E. Evaluation Protocol

The study presents application-level classification results, response time measurements for various weather conditions, results from a user satisfaction survey, and an estimation of urban mobility improvements. For reproducibility, these results should be classified into four types of evaluation:

(a) Correctness: determining if the route is valid and optimal with respect to the defined cost function.

(b) Predictive quality: comparing predicted travel times and congestion with actual travel times and conditions.

(c) Performance: measuring response latency and failure rate, as well as assessing resource usage.

(d) Mobility outcomes: comparing journey and fuel consumption times, changes in traffic throughput, user experience, etc.

Benchmarking should consider Dijkstra based on shortest path (in terms of distance and/or time), A* search based on an appropriate heuristic, and the complete multi-criteria routing. The evaluation should describe the size of the network, the origin and destination, the time of the day, the traffic situation, the time stamp of the input data, the cost function of the route, the route processing time, and the path selected. The study should state the length of time over which the actual traffic data are collected, and how journey times in real traffic conditions were recorded and measured.

IV. RESULTS REPORTED IN THE SOURCE THESIS

A. Route-Choice Illustration

Chapter 4 presents an example journey from Garrison to Eleme Junction during peak-hour traffic. Alternative routes were evaluated as follows: Route A (approx. 40 min); Route B (approx. 35 min), and Route C (approx. 45 min). Route B was used in this example to illustrate the model. The other routes have higher average congestion during peak-hour traffic. It is important to note that in practice, the routes have varying costs depending on the time of travel and the traffic conditions.

B. Response Time

The average response time during clear conditions is 2.1 seconds. During rain, it is 3.8 seconds; at night, 2.5 seconds; and during fog, 4.2 seconds. Longer delays during rain and fog are attributed to processing of environmental data associated with limited visibility. Another summary states the average response time is 3.15 seconds with a standard deviation of ±0.9 seconds. The results show that the interface was designed to generate responses in just a few seconds. A report meant for publication should state the total number of requests, identify the hardware and software used, and state the percentiles of latency, including median and 95th percentile, and indicate if measurements were made accounting for external delays (introduced by mapping APIs, etc.)

C. User Satisfaction

The thesis states that 500 users completed a user satisfaction survey made up of questions utilizing a 5-point Likert scale. It is a good start that the authors present this data, but it probably reflects just a minor part of the user experience. The survey assessed things like the accuracy of routes, the user interface, and recommendations. The mean satisfaction score was reported to be 4.3 out of 5. Like the authors state in the summary, they can't make generalizations to the whole population without justification. The authors need to check their sampling approach, the kind of participants they're including, the way they've recruited participants, missing responses, and the measurement scale. The authors should state the response distributions, confidence levels, and state the potential differences between private motorists

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and commercial drivers (for example, public transport users and others). The authors need to say what leads them to believe the outcomes represent user satisfaction.

Reported Mobility Outcomes:

If we look at the reported mobility outcomes, reductions of 18.4% in average commute times and increases of 22.1% in peak hour traffic throughput are reported. Also, a 12.9% improvement in fuel economy is reported. Benefits of this nature certainly reflect potential operational benefits, but their interpretation is limited to the scope and fidelity of the validation exercise. To justify making causal inferences, the study would need to describe the baseline, assumptions about the traffic demand, and the range of possible results given random seeds and variation in the simulation. While the authors note both field trials and simulations, the information presented is insufficient to provide an independent evaluation of the improvements attributed to each method. As such, the improvements should be reported as findings from the original research.

D. Classification Metrics and Consistency

One group of application-level metrics includes 98% accuracy, 91% precision, 96% recall, and a 99% F1 score. A different summary table includes mean values of 92% accuracy, 90% precision, 88% recall, and 89% F1 score. The reported F1 score of 99% is mathematically inconsistent with a precision of 91% and a recall of 96%, especially if the classical definition of harmonic mean is used to compute all three metrics. The harmonic mean of the values of 91% precision and 96% recall is approximately 0.934, that is 93.4% and not 99%. So the reported 99% F1 score is questionable until verified. F1 scores reported by classification reports usually indicate either a sampling issue or a computational mistake. The final manuscript needs to re-compute the metrics using the confusion matrix and state if the values reported are micro, macro, weighted, binary or class-specific averages.

V. DISCUSSION

This module shows the differences between route search and traffic prediction. Dijkstra and A* algorithms search for an optimal or near-optimal path in a graph by defining a cost function. These algorithms don't predict traffic conditions. The accuracy of route recommendations depends on the cost of edge, adequacy of heuristic, and representativeness of road network. So, an efficient system should integrate search for optimal or near-optimal path with traffic prediction and congestion estimation and display the timestamp and confidence level of predicted traffic.

Since, different users may have different preferences, a multi-criteria approach should be taken. For example, in the case of cargo transport, fleet operators may be more concerned with route reliability and fuel consumption, while emergency services may be more interested in lower travel times and access to certain roads. Commuters may want to ensure that their journey is more predictable, even if it means adding a little extra time to their travel. Flexibility to adjust recommended route weights may be used to determine whether minor changes in weights result in a different route being recommended. If the differences in costs of the alternatives are negligible, they should be shown as equal alternatives.

The reported response times show that the application has the potential to provide recommendations quickly. However, average response times don’t reveal the entire story. The 95th percentile latency and failure rate are important operational metrics and should be taken into account for peak usage. Mapping APIs and live data sources are out of the application’s control and can result in variable response times and service availability. Caching and fallback can be used to improve system reliability, but the system must identify outdated information.

The user satisfaction score is encouraging, and while it is good to see high perceived usefulness, it doesn’t tell us if the system has improved user mobility. Users may be satisfied with the system because of interface design or their expectations. Consequently, improvement in routing outcomes should be assessed separately. User trust could be improved with a prospective field study that balanced equal trips and road corridors, accounted for departure time and weather, and assessed user satisfaction with system recommended routes. We can also assess if the recommended routes improved user trust, fuel consumption and travel time.

The thesis discusses the potential disadvantages of the route recommendations. Although the recommendations lead to various benefits, such as shorter travel times, better traffic throughput, and improved fuel efficiency, there may be undesirable side effects on other parts of the road network. Route recommendations may shift congestions from one part of the road network to another. When a road network can be modeled, a routing system should try to optimize recommendations for all users, divide recommendations among different paths of similar costs, and not route vehicles

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through residential streets if this would put other road users, especially vulnerable road users, at risk. These considerations are relevant when optimizing and managing urban mobility.

VI. IMPLEMENTATION AND GOVERNANCE IMPLICATIONS

A route advisory system suited for operationnal use requires a road graph, a data-fusion service, a cost calculator, a route search engine, and an interface. Each component needs to be devised for independent testing. The road graph must represent various restrictions (i.e. one-way, left turns banned), closures, and distinctions between accessible and inaccessible links. Each of the traffic observations must be annotated with the source, timestamp, quality, and a retention policy.

Security and privacy deserve the same consideration because GPS data can reveal a user's home and work location, as well as other habits and patterns. Data must be collected only as required for the system to function. This data must be protected, stored securely, and only personnel from the transportation authority must have access. Aggregated traffic data must be used to ensure individual travel history is not collected and stored when not necessary. Security claims must be validated by testing instead of stating that the system is ready.

Any transportation authority considering deployment of the system across an entire city must have a supervised pilot program. The pilot program must use verified travel-time data as ground truth. The pilot program must establish means for users to report inaccurate route recommendations and procedures to manage incidents. Route recommendations must be treated as advisory. Human supervision must be employed during public events or road closures, and times when there is an interruption of service. Flooding must also be considered for supervision.

VII. LIMITATIONS

The source thesis describes a number of constraints including the absence of real time traffic data, inconsistencies with other sources, restriction to a particular geographical area, technology, time for collecting seasonal data, institutions, model validation, and unforeseen events. Due to the limitations described in the source thesis, conclusions from the empirical analysis may not be generalized. The source thesis, however, provides information regarding response times and user satisfaction. The sections used in this paper do not, however, provide enough detail to warrant independent replication. Consistency in the classification metrics also has to be addressed. The author has not developed new measurement of traffic or conducted an independent study. The paper, however, synthesizes and formalizes the design and findings of the original study.

VIII. RECOMMENDATIONS FOR FURTHER RESEARCH

The following research directions are suggested: (1) Make the road network and data dictionary publicly available; (2) Define edge costs and describe normalization methods; (3) Evaluate admissibility and consistency of heuristic with respect to selected cost function; (4) Compare A* and Dijkstra's algorithms under the same experimental conditions; (5) Take into account edge weights that vary with time and model delays due to incidents; (6) Study validation of routes and costs of paths as well as node expansions; (7) Evaluate time prediction errors using MAE and RMSE; (8) Study route travel time prediction for different time of the day, weather conditions and road class; (9) Describe survey procedures, user response distributions; and (10) Perform controlled field studies in order to evaluate recommendations to reduce travel times and ease congestion.

IX. CONCLUSION

This paper assesses the multi-criteria route recommendation module of an intelligent traffic advisory app developed for Port Harcourt. The module applies Dijkstra's algorithm for computing shortest paths, and A* for planning traffic aware routes, taking into consideration travel time, congestion, distance, fuel consumption and road hazards. The module is illustrated with a route planning example, average response time of 3.15 seconds, and an independent user evaluation rating of 4.3/5 with 500 participants. Other positive impacts expected from the module include potential reduction in travel time, improvement in traffic throughput, and fuel consumption. While the module is shown to have a positive impact, more experimental documentation is needed to support the findings. More independent verifications are required to establish the inconsistencies in the reported metrics. The primary contribution of the paper is showing how local traffic data can be combined with route-search algorithms to develop practical route planning systems, and to propose a research agenda to take an existing prototype of the system to provide reproducible urban mobility services and validate it under real world conditions.

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