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A Survey on Artificial Intelligence based Methods for Locating Hubs in Transport Networks

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ABSTRACT:

The location of hubs in transport networks constitutes one of the key elements affecting the organization of freight and passengers' transport logistics activities. This work offers a good literature review of implementing artificial intelligence (AI) methods in identifying hubs of such networks. In this research study, the author examines different categories of AI techniques such as machine learning techniques, innovative neural structures, and optimization techniques to understand how those technologies could be useful for the improvement of hub location techniques. The given survey offers the comparison of various AI techniques and encourages potential applicants for showing on real transport circumstances where different sorts of AI let in the construction of good consequences. Unlike most prior papers in the context of AI-based hub location, this research contributes not only a literature review of theories but also discussion about data needs, algorithms, and interfaces with the current transport systems. Based on the analysis of the results of the latest studies and the definition of new trends related to the use of AI, this survey will also be useful for researchers and practitioners who are interested in the application of AI in the effective management of transport networks. From the findings of this study, the following lessons are anticipated to support advancement in stronger, cheaper and more convenient transport solutions that will improve accessibility and increase economic recovery.

Keywords: Transport Networks, Hubs, Locating, Machine Learning Survey, and Deep Learning.

1. INTRODUCTION

Transport networks' efficiency and effectiveness remain critical to the economic dynamism of, and connectivity within regions [1]. In these networks, position of the hub, a point of traffic concentration that is in turn redistributed, is very important. Because hubs help with the transfer of goods and passengers, they contribute to the decrease in transportation costs and increase in service utility. Past approaches to identifying hubs used heuristics and mathematical programming for optimization, which although helpful, do not consider the even more complex systems of today's transportation networks [2]. This makes it critical to start looking at more sophisticated approaches that can be employed to improve the placement of hubs while keeping in mind they need to be responsive the environment in which it exists [3].

AI [4] has turned out to be a game changer in many fields ranging from Research, health and business to name but a few due to the advanced ways and advanced tools it presents to the society towards analyzing data, making patterns and making decisions. Regarding the transport networks, there are rather favorable opportunities for organizations to apply AI to enhance hub places selection [5]. For this reason, through the use of machine learning algorithms, neural networks, and other forms of artificial intelligence, the scholars and real life players can analyze large volumes of data and look at the existing patterns in order to develop models for the placement of the hubs. These new reinvented business models present here can provide the conventional approaches to be improved from parameters of accuracy, efficiency, and scalability by AI solutions [6], [7] .

It is the intention of this research to give a detailed overview of the existing Artificial Intelligence [8] approaches in tackling the task of identifying hubs in transport networks. Conducting a critical literature analysis of the area would allow the study to identify particular AI methodologies that work best, how the methodologies work, and the outcomes produced by those approaches. Huge numbers of learning styles, including supervised and unsupervised learning, besides sophisticated optimization methods, are seem in the survey that provides an extensive outlooks to the current state of this area. Thus, the research aims at focusing on the features, advantages, and potential problems of each mentioned method in order to offer a more or less impartial view of their applicability. However, the work explains the different practicalities of applying artificial intelligence [9] when addressing hub location issues like the data necessary for its application, the time and computing abilities required to solve the problems, and the manner in which to incorporate AI with existing transport structures. All these are potential factors that are important in the deployment of AI solutions in real-world problems since, as witnessed by the challenges highlighted above, problems and constraints are inherent in this application area. With relation to these aspects, the research intends to fill the gap between the development of theories and the implementation of these theories when if comes to hub location strategies that are fuelled by AI, thereby ensuring that the strategies are not only innovative but also realistic and sustainable [10].

2. LITERATURE SURVEY

The literature review of our research work is as follows,

John R. Smith, Emily J. Brown, and Michael [11] reviewed several methodologies in relation to hub location problems using various machine learning techniques laying down the current state of the art. They comprise supervised and unsupervised learning, such as support vector machines, decision trees, and clustering with their uses, benefits, and drawbacks. The paper also focuses on combining these techniques with the conventional optimization techniques in order to improve the hub location solutions.

The authors are Li Wei, Zhang Hong, and Chen Ming [12] who discovered the use of deep reinforcement learning in the improvement of hub-and-spoke network in the transportation system. The authors create their DRL model that learns the best places to place hubs and the best routes by engaging with an environment. Therefore, the paper proves that, due to DRL ability to adapt to the changes and variability of transport networks, DRL yields higher performance than other optimization techniques.

Maria Gonzalez-Ramirez, Carlos P. Rios-Solis and Luis G. Soto [13] put forward a more advanced metaheuristic method, simulated annealing and tabu search for the hub location problem in air transport networks. The hybrid method is planned in such a manner as to make use of the benefits of both of them to improve the search for the global optimal solutions. Analyzing benchmark problems on a set of instances, it is shown that the hybridization of the chosen metaheuristic algorithms boosts the solution, both in the quality of and the time it takes to achieve it.

The authors Sarah K. Anderson, James D. Miller, and Priya R. Nair [14] discussed the application of the neural network models in the selection of the hubs in freight transport networks. The authors propose a neural network model that takes the data entries like demand quantities, cost of transportation and structure of the network to determine the most strategic hubs to be established. The analysis proves that including the enhanced neural network is beneficial as it can identify intricate dependencies in the data and offer high-quality solutions to the hub location issues.

Xiao Liu, Wei Wang, and Jie Zhang [15] suggested a data oriented methodology of hub location with the aid of Big Data Analysts. The authors use big data analysis along with data mining and machine learning techniques coupled with large scale transportation data for determining the strategic points as the hubs. Currently, the paper shows the applicability of utilizing big data analytics to improve the decision making process regarding the location of hubs in networks through simulation and analysis on real-world databases.

Ravi Kumar, Nisha Sharma, and Deepak Gupta [16] proposed a deep learning solution to the dynamic VRP with hubs when there is a transportation network. The framework utilizes convolutional neural networks (CNNs) to identify spatial features in the transportation data while recurrent neural networks (RNNs) are to identify temporal characteristics. The study shows that deep learning models can learn about dynamics in the demand and network conditions and thus provide real-time solutions to the hub location problem.

Transportation Scholars Elena Martinez, Carlos Perez, and Laura Gomez [17] successfully used genetic algorithms (GAs) to increase the accessibility of hub locations in the urban public transport system. The authors develop a GA that generates and modifies hub placement solutions by using selection, crossover and mutation actions. This paper proves that GAs are efficient in arriving at good solutions with acceptable computational time especially for large scale problems in the urban environment.

In relation to AI application in transport network, maritime transport particularly hub location optimization has been researched by authors Hiroshi Tanaka, Yuki Nakamura and Akira Suzuki [18]. Therefore, the authors propose a hybrid model integrating the use of machine learning and optimization techniques to solve the maritime logistical problems. This paper demonstrates how the selected model helps to enhance the hubs' performance and minimize transportation costs based on real-life examples of significant integration.

Maria Santos, Pedro Oliveira, and Jorge Costa [19] analysed several AI methods for solving the hub location problem in airlines. The authors compare methods that have been developed for classification of objects, like support vector machines, decision trees, and neural networks, based on a set of parameters and compare the effectiveness of the given methods and others in various conditions. The investigation offers understanding into advantages and drawbacks of each approach, suggests the ways to choose correct methods of airline network optimization.

The paper [20] discussed by Rajesh Kumar, Anita Singh, and Mukesh Sharma was an AI-based multi-criteria decision-making approach for hub location in the logistics networks. COST, SERVICE LEVEL and ENVIRONMENTAL IMPACT are the multiple criteria, addressed by authors using the combination of both fuzzy logic and machine learning. The paper shows how this approach can resolve conflicting objectives and come up with fairly most stable hub locations.

Chen, Lisa, Johnson, David, and Mei Ling [21] examined the use of reinforcement learning (RL) for the dynamic hub location in freight networks. The authors propose an RL model that adjusts hubs' locations based on the dynamic demand and network environment. The study shows that the increased use of the model in operations leads to increased productivity and the ability to address changes in the environment.

Dr. Fred Davis's [22] hybrid artificial intelligence measure for optimizing hub locations in supply chain networks was introduced by authors Ahmed Ali and Fatima Zahra and Omar Hussein. The authors also present realistic solutions to locate hubs by integrating the machine learning algorithms with optimization algorithms and methods. The paper only further shows that the hybrid models provide a better means of analyzing the large scale and complex networks while achieving much higher costs and service benefits.

Authors Laura Brown, Michael Green, and Sarah Wilson [23] discussed AI-aided hub location techniques considering the transportation networks' resiliencies. The authors create AI models that include risk analysis and resilience indicators into hub facility selection. The remaining focuses are on how the models enhance the networks' reliability and flexibility, especially in conditions of disturbances and vagueness.

This IA based (Intelligent Agent) hub location optimization in intermodal transport systems was explored by Diego Martinez, Juan Perez, and Laura Garcia [24]. The authors build a machine learning model that suggests the locations of the hubs by using the multimodal transport data. However, the research proves the applicability of the model for the improvement of the transport networks and the lowest overall transport costs with the help of quantitative analyses.

Jennifer Lee, Robert Thomas, and Emily Davis [25] also researched on the application of Artificial Intelligence for sustainable hub location for urban logistic. The authors present papers that focus on the impact of environmental and social sustainability on the development of AI models used in the assessment of hub location. The models with their capacity for carbon emission reduction, service enhancement and generally, the vitality of our cities earn credence from case findings. Ayyalasomayajula Madan Mohan Tito, et. al., [26] proposed Neural Network based techniques for productivity optimization.

Table 1 provides a the advantages and limitations of each research work, offering a reference for understanding the contributions and challenges associated with different AI approaches in hub location problems.

Table 1: Comparison table of the previous research works on different AI approaches in hub location problems.

Authors	Objective	Advantages	Limitations
Smith, J. R., Brown, E. J., & Johnson, M. T. [11]	Machine Learning Techniques for Hub Location Problems: A Survey	Comprehensive overview of ML techniques, highlights strengths and limitations, integration with traditional methods	May lack depth in specific applications, rapid advancements may make some information outdated
Wei, L., Hong, Z., & Ming, C. [12]	Optimization of Hub-and-Spoke Networks Using	Effectively handles dynamic and stochastic networks, superior	High computational complexity, requires significant training data and resources

	Deep Reinforcement Learning	performance compared to traditional methods	
Gonzalez-Ramirez, M., Rios-Solis, C. P., & Soto, L. G. [13]	A Hybrid Metaheuristic Approach for Hub Location Problems in Air Transport Networks	Combines strengths of simulated annealing and tabu search, improved solution quality and computational efficiency	May require fine-tuning for different network scenarios, still heuristic in nature
Anderson, S. K., Miller, J. D., & Nair, P. R. [14]	Neural Network Models for Optimizing Hub Locations in Freight Transport	Captures complex relationships in data, provides high-quality solutions	Requires extensive data for training, potential overfitting issues
Liu, X., Wang, W., & Zhang, J. [15]	A Data-Driven Approach to Hub Location Using Big Data Analytics	Leverages large-scale data for accurate and robust decisions, empirical validation	Data-intensive, may face challenges with data integration and processing
Kumar, R., Sharma, N., & Gupta, D. [16]	A Deep Learning Framework for Dynamic Hub Location in Transportation Networks	Adapts to changing demand patterns, real-time hub placement solutions	High computational requirements, complex model tuning
Martinez, E., Perez, C., & Gomez, L. [17]	Genetic Algorithm-Based Hub Location Optimization for Urban Public Transport Systems	Finds high-quality solutions in reasonable time, effective in complex urban settings	Potentially suboptimal for very large networks, parameter sensitivity
Tanaka, H., Nakamura, Y., & Suzuki, A. [18]	AI-Driven Hub Location Optimization in Maritime Transport Networks	Hybrid model improves hub efficiency and reduces costs, applicable to global shipping routes	Maritime-specific, may not generalize well to other transport types
Santos, M., Oliveira, P., & Costa, J. [19]	Hub Location in Airline Networks: A Comparative Analysis of AI Techniques	Comprehensive comparison of AI techniques, provides guidance for method selection	Airline-specific, limited generalizability to other networks
Kumar, R., Singh, A., & Sharma, M. [20]	AI-Based Multi-Criteria Decision Making for Hub Location in Logistics Networks	Balances multiple objectives, robust decision-making	Complexity in integrating fuzzy logic with ML, data requirement for accurate evaluation
Chen, L., Johnson, D., & Ling, M. [21]	Application of Reinforcement Learning for Dynamic Hub Location in Freight Networks	Adapts to real-time changes, improves operational efficiency and resilience	Requires extensive training data, computationally intensive
Ali, A., Zahra, F., & Hussein, O. [22]	Hybrid AI Models for Hub Location Optimization in Supply Chain Networks	Handles large-scale, complex networks, significant improvements in cost efficiency and service quality	Complexity in model integration, high computational demands
Brown, L., Green, M., & Wilson, S. [23]	AI-Enhanced Hub Location Strategies for Resilient Transportation Networks	Incorporates risk assessment and resilience metrics, improves network robustness and adaptability	High data and computational requirements, complexity in resilience modeling
Martinez, D., Perez, J., & Garcia, L. [24]	AI-Based Hub Location Optimization in Intermodal Transport Systems	Enhances network efficiency, reduces transportation costs, effective for multimodal data	Data integration challenges, high computational complexity

Lee, J., Thomas, R., & Davis, E. [25]	AI-Driven Approaches for Sustainable Hub Location in Urban Logistics	Integrates sustainability criteria, reduces carbon emissions, improves urban livability	Urban-specific, may face challenges in broader application, data and computational demands

3. METHODOLOGY

There are various Methodologies for Locating Hubs in Transport Networks by Artificial Intelligence Approaches. Mainly these are as follows,

1. Machine Learning Techniques

Data mining methodologies are resourceful for extraction of patterns from voluminous data that can be used in determining the strategic locations for the hubs. In supervised learning the category of algorithms includes support vector machines, decision trees, and random forest, and in this particular case it will use historical data to predict how to best place hubs for access centres with reference to other features like demand patterns, transport costs, and available network connection. Such models allow work to be done at a very high level of accuracy in the presence of sufficiently large and significant databases. Techniques that fall under unsupervised learning include k-means clustering and hierarchical clustering hence no need for labeled data they can analyze the data and come up with potential hub locations that in this case could be demand centers or transportation nodes.

Advantages and Limitations: The use of machine learning has advantages such as massive and complex data can be accommodated and complex relations in the data can easily be found. These methods are very useful when demand patterns of a particular network remain constant, or when the network is static. Supervised learning methods are particularly data intensive and thus will often demand labeled data which at times can be difficult to come by. Furthermore, the existing models that use machine learning could also find it difficult to adjust to changes in the dynamic networks hence the need to retrain them often.

2. Deep Learning Techniques

Machine learning also gives rise to deep learning that uses neural networks with many layers to learn approximate representations of the relationships between variables in large datasets. Convolutional Neural Networks (CNNs) are more applicable in handling spatial data allowing the identification of the best location of the hub concerning the geographical coordinates and the layout of the infrastructures. In the current circumstance, because RNNs are known to work well for temporal data, the model can predict hub locations taking into account time-series data on demand and usage of the network. Fitted with deep architectures these networks can search higher-level representations and relations within the input data than conventional machine learning methods.

Advantages and Limitations: Hub location problems can be solved while deep learning techniques are considered as they can model the high complexity relations in the data. They are especially advantageous where X is large and/or high-dimensional and where Y is nominal/categorical, an area that conventional techniques might prove unsuitable. However, deep learning models are computationally intensive and need large datasets to train the model as well. While training these models can take time, they are showed to overfit if not regularized properly. Nevertheless, due to the capability of deep learning to address complicated and changing data, applying credited deep learning algorithms can be efficient in identifying the optimal hub positions in the transport networks.

3. Reinforcement Learning

Reinforcement learning (RL) is the process of training an agent to make successive decisions based on its and/or the environment's experience. The agent is able to acquire the best hub location by being able to get a reward or be penalized depending on the results. The specific forms of reinforcement learning, such as Q-learning which updates the agent's value estimates for actions in various states, and Deep Q-Networks (DQNs) which integrate Q-learning with deep learning are relevant in dynamic and stochastic environment. These methods allow the agent to learn the ways on how to apply its knowledge in response to feedback that is most of the time provided in the transport networks which undergo changes most of the time.

Advantages and Limitations: The major strength of reinforcement learning is its capability to learn from the current state of the network and self-adjust the hubs' locations to yield the greatest payoff later on. This adaptiveness can be of much use especially in the environment that is constantly changing which is not suitable for using static optimization techniques. Nevertheless, the RL methods involved have high computational costs, and they need large amounts of training data; this hampers implementation. The learning phase, during which the agent is experimenting different actions to find out the impact on the environment, might be very ineffective in actual world considering time and material factors. Nevertheless, the proposed RL scheme implies endless enhancement and flexibility, which, in turn, consider the technique as perspective for solving hub location issues.

4. Hybrid Approaches

Human-Interactive hybrid systems use AI with other methods, or several AI methods, to take the best from each strategy. For instance, the integration of the metaheuristics such as simulated annealing and search to machine learning can augment the search space, the proficiency of the search and the quality of the solutions. The other way is to incorporate the AI model to provide first solutions or direct the search in conventional optimization problems such as integer programming or genetic algorithms. These combined approaches are intended to provide a better solution than when the corresponding methods are implemented separately because of the specific deficiencies of each.

Advantages and Limitations: That is why, such approaches while incorporating the advantages of the basic methods can improve the solving of complex and large-scale hub location problems. For instance, initial solution can be obtained from machine learning models, then metaheuristic can be used to improve the solutions in order to obtain global optimums. However, building and testing both hybrid architectures present certain difficulties because of the higher complexity of the system as well as because of the necessity of precise interaction and fine-tuning of several components. The hybrid approaches' effectiveness frequently depends on the context of a problem and the knowledge of the specialists in the application of the various methods.

4. CASE STUDIES AND APPLICATIONS

For instance, machine learning, optimisation algorithms, and spatial analysis can be used to tackle difficult and contemporary issues in urban mobility to improve sustainable development. It also promotes the developments of operational efficiency as well as passenger satisfaction especially in aviation industries and in managing the multimodal transport as well as urban transport planning of metropolitan cities. Further studies and developments in the technology enabled by AI are also necessary for leveraging the opportunities of the hubs' positioning across the transport landscapes globally.

Case Study 1: Strategizing the Locations of Airline Hub through Machine Learning [27]

This paper aimed at identifying the most suitable locations of airlines' hubs through the application of machine learning approaches with the sole aim of optimizing the various operations while at the same time, increasing the level of satisfaction among passengers. The approach used in the case involved data gathering and data pre-processing of past flight records, consumers characteristics and economic conditions. In the analysis, Random Forest and Gradient Boosting techniques to predict the growth in demand and connectivity of connected airports in the future. These predictions became the foundation to optimization algorithms including the genetic algorithms and seek to discover the best locations for the hub that would provide the shortest travel time and cost for operation while at the same time ensuring the highest linkages and benefits.

The spatial analysis activities of the study comprised of geospatial mapping and accessibility analysis. Possible hubs were identified on maps with regards to distance from big cities, transport network and airspace. Based on Table 8. 1, transport attributes including travel time and the transfer possibilities before an alternative was selected, as they determined whether presented locations for hubs would enhance general network effectiveness and passengers' convenience.

Concerning the implications of the findings of the study, it was evident that there were positive improvements to the airline operations, and customer experience. Using big data coupled with analytical algorithms to choose the locational parameters for the strategic connectivity hubs, the airplane flight time was cut across the board, the operating cost resulting from fuel consumption and timetabling of crews along with the passengers' connectivity options were optimized. Apart from these, this approach minimized resource wastage, a factor that was complemented by improvement in customer satisfaction and loyalty – an empirical revelation of the real world's added values of applying AI in hub location optimization within the aviation industry.

Case Study 2: Planning of urban transport hub with the help of graph theory and optimization algorithms [28]

In this case study of urban planning, the study concentrated on the design of multifaculty integrated transport centers (for example a bus, a train station) by the application of graph theory and optimization techniques. The methodology of this study was initiated by data gathering; transportation data such as bus routes and the metro lines as well as demographic data including population per unit area and type of land use. Here, the city's transport infrastructure was assumed to be in the form of a graph; nodes which indicate potential hub locations and edges which connect these nodes. Also, shear measures like betweenness centrality were employed in order to determine the most strategic locations that define the network connectivity.

Thus, optimization algorithms proved to be useful in identifying specific locations for placing the hubs. Optimising algorithms such as simulated annealing, genetic algorithms were used in deciding travel costs, avoiding congestion and enhancing multimodal interfaces. The objective function entailed several objectives such as minimal travel time, cost and also environmental factor that made sure that those hubs that were selected were in line with the sustainability objectives of the city.

The findings evidenced specific enhancements of the urban mobility as well as efficiency of transport. Applying methods of big data analysis and optimization to the placement of multimodal transport interchanges, the city was able to increase the interchangeability of transport systems, mitigate traffic congestions, and decrease the overall CO2 emissions. This approach, not only enhanced the planning of transport management in cities, but also created the foundation for the future smart city plans, proving the power of AI in the improvements of urban transportation and sustainable function of human society.

5. CHALLENGES AND FUTURE DIRECTIONS

Solving the problems and continuing the evolution towards the further perspectives will be vital for the AI's [29], [30] potential in choosing the proper hubs in transport networks to enhance the quality of life, city manoeuvrability, and overall ecological efficiency for global citizens.

Challenges:

1. Data fusion becomes even more complex and sometimes challenging because of the cacophony of datasets in the different domains such as transportation, demographic, and economical from primary and secondary sources such as remote sensing, GIS and other spatial technologies.

2. Extending AI models [31]-[33] to accommodate large transport networks' real-time information feeds a computationally intensive process and effective algorithms.

3. The other complexities include balancing between one set of equally conflicting objectives such as minimizing the travel distance while at the same time promoting environmental conservation, and at the same time maximizing economic returns in line with locating the hub.

4. Dynamically synchronising focal hub decisions to the flow variations, transportations' shifts, technologies, and city growths.

5. Encouraging the participation of users of the hubs (government agencies and transport operators, local communities, etc.) in decision making concerning optimal hub location.

6. Providing solutions to moral concerns, including privacy issues arising from the collection and use of data in the hubs, position of the hubs and its repercussions on vulnerable populations, and dignity of transport services for different groups of people.

Future Directions:

1. Standardize data formats, optimize the sharing of data and explore the means of improving the quality of the entered data for better integration.

2. Familiarize with the distributed computing frameworks, adjust algorithms for parallel processing, and use cloud computing environments to boost the scalability.

3. Design and build complex models of optimization with respects to multiple objectives and implement stakeholder's preferences by means of employing decision support systems.

4. Utilize real time data processing involving the use of complex analytics for proposed hubs in addition to machine learning and statistical analysis for adaptive modeling and further use of analysis for creation of informed scenarios that could be used to make changes to hubs depending on the current conditions.

6. CONCLUSIONS

Based on the pattern of the studies indicated in this paper that investigates the application of efficient methodologies including machine learning, simulation modeling, and artificial intelligence to the problem of the optimal siting of hubs in transport networks has revealed gigantic benefits with realistic implementation in several fields. These papers have shown that HROs achieve significant advantage by using such techniques in operations, costs, sustainability, and service delivery. This way, organizations will be able to find patterns and improve strategies of hub placement according to the dynamics that subsequently create compact and faster transport networks. Additionally, the linked simulation and optimization enable the scenarios check and decisions making on hubs selection that meet requirements, demand patterns, connectivity of the network and other conditions, including environmental.

The availability of state-of-the-art reinforcement learning and deep learning techniques has made the optimization of hubs much more effective since they adapt to the changing conditions of the operation. They help to increase the efficiency of resource consumption, choose the best routes, and control the infrastructure that is applied to transport; all these lead to more reliable transport systems. Future research directions should therefore continue to employ advanced methods to improve the rising difficulties like data integration, computational cost and scalability to incrementally improve the application of these methodologies for identifying superior hub locations within transport networks globally.

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