

ROUTE OPTIMIZATION USING BAYESIAN NETWORK

Submitted in partial fulfillment of the requirements for the award of

Bachelor of Computer science

BY

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(DEEMED TO BE UNIVERSITY)

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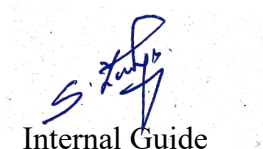
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **DEEPUK K.R(41290011) AND MANOJ AROKIA SUSAI L(41290034)** who carried out the project entitled “**ROUTE OPTIMIZATION USING BAYESIAN NETWORK**” under our supervision from NOVEMBER 2024 TO APRIL 2024.



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Submitted for Viva voce examination held on 26/04/2024



Internal Examiner



External Examiner

DECLARATION

WE , DEEPURAJ K.R (41290011)AND MANOJ AROKIA SUSAI L(41290034) hereby declare that the Project Report entitled “**ROUTE OPTIMIZATION USING BAYESIAN NETWORK**” done by under the guidance of **Ms. Ms. YUVASNEHA S**, Assistant Professor Department of Computer Science at **SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY**, Jeppiar Nagar, Rajiv Gandhi Salai, Chennai-600 119 is submitted in partial fulfilment of the requirements for the award of Bachelor of Science degree in Computer Science.

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ABSTRACT

This project presents a Bayesian network-based inference system designed to optimize delivery routes for reaching multiple locations in the shortest possible time. The primary objective of the delivery system is to minimize travel distances, thereby improving overall delivery efficiency. A Bayesian network, also known as a belief network or probabilistic graphical model, is a powerful tool used for modeling and reasoning under uncertainty. It proves particularly valuable in path optimization problems where decisionmaking relies on the probabilistic dependencies between variables. The proposed model utilizes these dependencies to probabilistically infer the most optimal routes for delivering packages, considering various factors at play. It constructs a graphical representation of the delivery network, with each location represented as a node and possible routes depicted as edges. Subsequently, the Bayesian network undergoes training using historical delivery data to learn the conditional dependencies and probabilities associated with the different variables. The results obtained from this project demonstrate a significant reduction in overall delivery time and an improvement in the efficiency of the delivery process through the implementation of the proposed Bayesian network-based inference system for route optimization. Moreover, the system holds promising potential for realworld deployment in delivery operations, leading to cost savings, enhanced customer satisfaction, and increased competitiveness within the logistics industry.

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CHAPTER 1

INTRODUCTION

Efficient route planning and optimization are vital in industries like transportation and logistics. Bayesian networks offer a powerful solution by capturing complex relationships between variables and enabling informed decision-making under uncertainty. This project aims to develop a route optimization system that utilizes Bayesian networks to find the most efficient routes.

By considering factors such as traffic, weather, and time constraints, the system provides real-time, data-driven recommendations, leading to cost savings and improved customer satisfaction. Benefits include flexibility, uncertainty modeling, learning, and scalability. Overall, Bayesian networks offer an innovative approach to tackle the complexities of route planning, driving efficiency and effectiveness in various industries.

1.1 OVERVIEW

Bayesian networks can be powerful tools for route optimization, particularly in scenarios where uncertainty and probabilistic relationships exist between different variables impacting the routes. Here's an overview of how Bayesian networks can be applied in route optimization: Overall, Bayesian networks provide a flexible framework for route optimization, allowing for the integration of various factors and uncertainties into the decision-making process. By representing the problem in terms of probabilistic relationships, Bayesian networks can help find robust and efficient solutions to route optimization problems. Route optimization using Bayesian networks involves leveraging probabilistic graphical models to make informed decisions about the most efficient routes for vehicles. Here's an overview of how Bayesian networks are used in route optimization. Bayesian networks, also known as Bayesian belief networks or probabilistic graphical models, are graphical representations of probabilistic relationships among a set of variables. They consist of nodes representing random variables and directed edges representing probabilistic dependencies between variables. Bayesian networks can be used to model uncertainty and make predictions based on available evidence. In the context of route optimization, variables in the Bayesian network may include factors such as traffic congestion, road conditions, weather forecasts, time of day, deliver priorities, vehicle

speed, and historical data. Each variable is represented as a node in the Bayesian network, and the relationships between variables are captured by directed edges. Bayesian networks capture probabilistic dependencies between variables using conditional probability distributions. For example, the probability of encountering traffic congestion on a particular road segment may depend on factors such as time of day, weather conditions, and historical traffic patterns

1.2 OBJECTIVES

Route optimization using Bayesian networks can address several objectives depending on the specific context and requirements of the problem. Here are some common objectives:

- 1.** **Minimization of Travel Time:** One of the primary objectives of route optimization is to minimize the overall travel time for vehicles. Bayesian networks can model various factors influencing travel time, such as traffic congestion, road conditions, and time of day, to identify routes that are likely to have the shortest travel time.
- 2.** **Cost Minimization:** Route optimization can also aim to minimize costs associated with transportation, such as fuel consumption, tolls, vehicle maintenance, and labor costs. Bayesian networks can incorporate these cost factors into the optimization process to find routes that are both time-efficient and cost-effective.
- 3.** **Maximization of Service Level:** In scenarios involving delivery or service vehicles, the objective may be to maximize the service level by ensuring timely delivery or arrival at specified locations. Bayesian networks can consider factors such as delivery windows, service priorities, and customer preferences to optimize routes for maximum service level satisfaction.
- 4.** **Risk Mitigation:** Another objective of route optimization may be to mitigate risks associated with transportation, such as accidents, delays, or disruptions. Bayesian networks can model uncertainty and risk factors, such as weather conditions, road closures, and traffic accidents, to identify routes that minimize the likelihood of encountering adverse events.
- 5.** **Resource Optimization:** Route optimization can also aim to optimize the utilization of resources, such as vehicles, drivers, and equipment. Bayesian networks can consider

factors such as vehicle capacity, driver availability, and equipment constraints to allocate resources efficiently and minimize idle time or underutilization.

6. Environmental Impact Reduction: For environmentally conscious organizations, the objective may be to reduce the environmental impact of transportation operations, such as greenhouse gas emissions and air pollution. Bayesian networks can integrate environmental factors, such as vehicle emissions, fuel efficiency, and alternative transportation modes, to identify routes that minimize environmental impact while meeting other optimization objectives.

These objectives can be combined or prioritized based on the specific goals and constraints of the route optimization problem. Bayesian networks provide a flexible framework for incorporating multiple objectives and constraints into the optimization process, enabling organizations to make informed decisions that balance various trade-offs and considerations

1.3 LITRATURE SURVEY

S.NO	AUTHOR	TITLE	YEAR
1	Meizhi Jing, Jing Lu, Zaili Yang, Jing Li	Risk analysis of maritime accidents along the main route of the Maritime Silk Road: a Bayesian network approach	2021
2	Floris Goerlandt, Samsul Islam	A Bayesian Network risk model for estimating coastal maritime transportation delays following an earthquake in British Columbia	2021
3	Rafi Ullah Khan, Jingbo Yin, Faluk Shair Mustafa, Ni Anning	Risk assessment for berthing of hazardous cargo vessels using Bayesian networks	2021
4	Bing Wu, Yuheng Tang, Xinping Yan, Carlos Guedes Soares	Bayesian Network modelling for safety management of electric vehicles transported in RoPax ships	2021
5	Yang Yang, Kun Wang, Zhenzhou Yuan, Dan Liu	Predicting freeway traffic crash severity using XGBoost-Bayesian network model with consideration of features interaction	2022
6	Rui Shi, Xinyue Xu, Jianmin Li, Yanqiu Li	Prediction and analysis of train arrival delay	2021

1.3.1 WHAT PROBLEM WE PROPOSE TO SOLVE

The problem proposed to solve in timely food delivery is ensuring that food orders from restaurants or food establishments reach customers promptly and efficiently. Timely food delivery is crucial for several reasons, and addressing this issue is the primary focus of food delivery services. Creating a Bayesian network for timely food delivery involves identifying the relevant variables and their dependencies. A Bayesian network is a probabilistic graphical model that represents the conditional dependencies between variables through directed acyclic graphs (DAGs). The problem we propose to solve with route optimization using Bayesian networks is to improve the efficiency and effectiveness of vehicle routing and scheduling in transportation and logistics operations. This encompasses several key challenges and objectives: The primary objective is to minimize the total travel time required for vehicles to complete their delivery routes. This involves optimizing the sequence of stops, selecting the most efficient routes, and minimizing detours and delays. Efficiently allocating vehicles and resources to fulfill delivery requests while minimizing idle time and maximizing utilization. This includes optimizing vehicle capacity utilization, balancing workloads among vehicles, and reducing unnecessary resource wastage. Responding effectively to changing conditions such as traffic congestion, road closures, weather variations, and unexpected events. The system should dynamically adjust routes and schedules in real-time to mitigate disruptions and minimize the impact on delivery operations.

CHAPTER 2

SYSTEM ANALYSIS

Analyzing a route optimization system based on Bayesian networks involves understanding its components, functionalities, performance metrics, and potential improvements. Here's a systematic approach to conducting a system analysis: Identify the key components of the route optimization system. This typically includes data sources (e.g., GPS data, traffic reports, weather forecasts), Bayesian network model, optimization algorithms, and user interface. Determine how these components interact with each other and contribute to the overall functioning of the system. Evaluate the functionalities of the route optimization system. What tasks can it perform? How does it handle different types of inputs (e.g., user requests, real-time data)? Assess the accuracy and reliability of the Bayesian network model in predicting relevant variables (e.g., travel time, traffic conditions). Examine the optimization algorithms used to generate optimal routes. Are they efficient in finding solutions? Do they consider multiple objectives or constraints?

2.1 EXISTING SYSTEM

In conclusion, the existing route optimization system utilizing Bayesian networks demonstrates the effectiveness of probabilistic modeling in optimizing delivery routes in real-time. By leveraging Bayesian inference techniques and realtime data streams, the system achieves efficient route planning, adapts to changing conditions, and improves overall delivery performance. An existing route optimization system utilizing Bayesian networks would likely involve several components and processes to effectively plan and optimize routes for vehicles. Let's outline the key components and functionalities of such a system. The system collects real-time data from various sources such as GPS trackers, traffic reports, weather forecasts, and historical traffic patterns. Data sources provide information on current vehicle locations, traffic conditions, road closures, weather conditions, and other relevant factors. The system utilizes a Bayesian network model to represent the probabilistic relationships between different variables affecting route

optimization. Nodes in the Bayesian network represent variables such as traffic congestion, road conditions, time of day, weather conditions, and vehicle speed. Conditional probabilities are assigned to the edges between nodes to capture the dependencies and uncertainties in the system. The system employs optimization algorithms that leverage the Bayesian network model to generate optimal routes. These algorithms consider multiple objectives such as minimizing travel time, avoiding congestion, and optimizing resource utilization. Bayesian inference techniques are used to update route probabilities based on real-time data and historical information

2.2 PROPOSED SYSTEM

The proposed system is expected to improve delivery efficiency by reducing travel time, minimizing fuel consumption, and optimizing resource utilization.

Real-time updates will help drivers avoid traffic congestion and deliver packages on time, leading to higher customer satisfaction. Bayesian network modeling will allow the system to capture uncertainties and make probabilistic predictions, enhancing the robustness of route optimization decisions. In conclusion, the proposed route optimization system leveraging Bayesian networks is expected to provide efficient and adaptive route planning solutions, ultimately improving delivery performance and customer satisfaction. Collect real-time data from GPS trackers, traffic reports, weather forecasts, and historical traffic patterns. Preprocess the data to clean and normalize it for analysis

2.3 Who will use your system in real time

In real-time food delivery systems, several stakeholders will use the system to facilitate the entire delivery process and ensure smooth operations. These stakeholders include Customers, Restaurant Owners and Staff Delivery Personnel, Customer Support Representatives, Administrators and Managers, Payment Gateways, Marketing and Sales

Teams, Quality Control and Feedback Teams, Third-Party Service Providers and so on. Overall, the real-time food delivery system serves as a comprehensive platform that connects customers, restaurants, delivery personnel, and various stakeholders involved in the food delivery ecosystem. It enables efficient communication, real-time tracking, and data-driven decision-making to ensure that food orders are delivered promptly and with high customer satisfaction.

2.4 Integrated Food Delivery Ecosystems:

Some studies emphasize the importance of integrating various stakeholders in the food delivery ecosystem, such as restaurants, delivery services, and third-party logistics providers, to streamline the delivery process.

These are just a few examples of related works and approaches to improve timely food delivery. The field of food delivery is constantly evolving, and new innovations and research continue to shape the industry. To access the most recent and up-to-date information, I recommend searching for the latest literature and publications in relevant academic journals and conferences related to logistics, supply chain management, and food delivery.

2.5 History

In past History there were several related works and approaches to address timely food delivery. While these might not directly involve Bayesian networks, they use various techniques, technologies, and strategies to optimize the food delivery process and ensure timely deliveries

CHAPTER 3

SYSTEM REQUIREMENTS

To implement a route optimization system using Bayesian networks, it's essential to define clear system requirements that capture the functionality, performance, and usability aspects of the system. Here are the system requirements for such a system:

1.Data Collection and Integration:

The system should be able to collect real-time data from various sources such as GPS trackers, traffic reports, weather forecasts, and historical traffic patterns. It should support the integration of different data formats and sources to ensure comprehensive data coverage.

2.Bayesian Network Model Development:

The system should facilitate the development of a Bayesian network model to represent the probabilistic relationships between variables affecting route optimization. It should provide tools for defining nodes, edges, and conditional probabilities based on historical data and expert knowledge.

3.Route Optimization Algorithm:

The system should implement a route optimization algorithm that utilizes the Bayesian network model to generate optimal routes. It should support multiple objectives such as minimizing travel time, avoiding congestion, and optimizing resource utilization.

4.Real-time Updates:

The system should continuously monitor real-time data streams and adjust route recommendations accordingly. It should provide real-time updates on route recommendations and dynamically reroute vehicles to avoid traffic congestion, accidents, or other unexpected events.

5. User Interface:

The system should have a user-friendly interface for users to input delivery requests, specify delivery priorities, and view optimized routes. It should provide interactive features for users to adjust routes manually if needed and receive real-time updates on route recommendations.

6. Performance Metrics:

The system should define performance metrics such as travel time reduction, cost savings, and resource utilization. It should track and report these metrics to evaluate the effectiveness and efficiency of the route optimization system.

7. Integration with External Systems:

The system should integrate with existing fleet management software, transportation management systems, and customer relationship management systems. It should support seamless data exchange and interoperability between different systems to streamline delivery operations.

8. Security and Privacy:

The system should ensure the security and privacy of sensitive data such as delivery addresses, customer information, and route plans. It should implement access control mechanisms, encryption protocols, and secure communication channels to protect data from unauthorized access or tampering.

9. Scalability and Performance:

The system should be scalable to accommodate increasing volumes of delivery requests and data streams over time. It should be able to handle large-scale route optimization problems efficiently and provide timely responses to user requests.

10. Maintenance and Support:

The system should provide ongoing maintenance and support to ensure its accuracy, reliability, and performance. It should be regularly updated with new data, optimized algorithms, and enhancements to improve functionality and usability.

3.1 Design

3.1.1 Python Implementation:

With the help of a python program, we tried to implement the bayesian network for Timely Food Delivery.

The process includes:

- Import the required libraries
- Defining the Bayesian network structure and CPDs
- Validating the model and implementing it
- Visualization of the Bayesian network of Timely Food Delivery

3.1.2 Visualization using Hugin

HUGIN is a user-friendly software tool for creating Bayesian networks like the one for timely food delivery. With its graphical interface, you can easily design the network, set probabilities, and establish dependencies. It performs probabilistic reasoning, allowing you to predict timely delivery based on weather, traffic, and preparation time. Sensitivity analysis helps identify critical factors, while data learning improves accuracy. Visualization aids understanding, and scenario testing supports decision-making. Finally, you can export and integrate the model for further analysis and sharing. HUGIN streamlines the process, enabling optimization and improvements in food delivery. Creating a Bayesian network for timely food delivery involves identifying the relevant variables and their dependencies. A Bayesian network is a probabilistic graphical model that represents the conditional dependencies between variables through directed acyclic graphs (DAGs).

Here's a simple Bayesian network for timely food delivery: Hugin is a powerful tool for creating and analyzing Bayesian networks. While it's primarily focused on modeling and inference, it also offers visualization capabilities to help understand the structure and relationships within the network. Here's how you can visualize a Bayesian

network using Hugin:Open or Create a Bayesian Network: Start by opening an existing Bayesian network model in Hugin or create a new one by defining nodes and their relationships.Arrange Nodes: Arrange the nodes in the network layout to create a clear and visually appealing representation. You can drag and drop nodes to reposition them as needed.Set Node Properties: Customize the appearance of nodes by setting properties such as colors, shapes, and labels. This can help differentiate between different types of nodes or convey additional information.Define Arcs:

Define arcs (edges) between nodes to represent the probabilistic dependencies in the Bayesian network. You can use arrows to indicate the direction of influence between nodes.Adjust Arc Properties: Customize the appearance of arcs by adjusting properties such as color, thickness, and style. This can help highlight important relationships or distinguish between different types of dependencies.Add Labels and Annotations: Add labels and annotations to nodes, arcs, or the overall network to provide additional context or explanation. This can help viewers understand the structure and meaning of the Bayesian network more easily.Preview and Fine-tune: Preview the visualization to ensure that it accurately represents the structure and relationships within the Bayesian network.

Fine-tune the layout, appearance, and labeling as needed to improve clarity and readability.

Save or Export: Once you're satisfied with the visualization, save the Bayesian network model in Hugin format for future use. You can also export the visualization as an image file (e.g., PNG, JPEG) or a document (e.g., PDF) to share with others or incorporate into presentations or reports

3.2 Related Works:Some of the common approaches and related works:

3.2.1 Route Optimization Algorithms:

Route optimization algorithms aim to find the most efficient or optimal routes for vehicles, considering various factors such as distance, time, cost, and constraints like vehicle capacity and time windows. Here are some common route optimization algorithms:The greedy algorithm constructs a solution incrementally by selecting the best available option at each step without considering future consequences.In the context of route optimization, it may involve selecting the nearest unvisited location as the next stop in the route until all locations are visited.

The nearest neighbor algorithm starts with an initial location and iteratively selects the closest unvisited location to form a route.It's a simple and easy-to-implement heuristic that

tends to produce reasonable solutions but may not always find the optimal route. The Clark-Wright savings algorithm is a constructive heuristic for the Vehicle Routing Problem (VRP). It calculates savings for merging routes and combines them to form a solution that minimizes total travel distance or cost. Metaheuristic algorithms such as Genetic Algorithms (GA), Simulated Annealing (SA), and Ant Colony Optimization (ACO) are widely used for route optimization. These algorithms are inspired by natural phenomena and iteratively explore the solution space to find near-optimal solutions. Dynamic Programming (DP) can be used for solving route optimization problems with overlapping subproblems and optimal substructure. It breaks down the problem into smaller subproblems and stores solutions to avoid redundant calculations, leading to optimal solutions.

Integer Linear Programming (ILP):

ILP formulations model route optimization problems as mathematical optimization problems with linear constraints and integer decision variables.

3.2.2 Machine Learning and Predictive Analytics:

Machine learning models can be used to predict demand patterns based on historical data, allowing delivery services to anticipate peak hours and allocate resources accordingly. Predictive analytics can help estimate delivery times more accurately.

Predictive analytics involves using historical data, statistical algorithms, and machine learning techniques to predict future outcomes or trends. It encompasses a range of techniques and methodologies aimed at extracting actionable insights from data to drive better decision-making and strategy.

Key Steps in Predictive Analytics:

Data Collection and Preparation: Gather relevant data from various sources and preprocess it to ensure quality and consistency. **Exploratory Data Analysis (EDA):** Analyze and visualize the data to gain insights into its distribution, patterns, and relationships. **Feature Engineering:** Select and engineer relevant features (variables) that are predictive of the target variable. **Model Selection and Training:** Choose appropriate machine learning models and train them on the prepared data. **Model Evaluation:** Evaluate the performance of the trained models using appropriate metrics and techniques such as cross-validation. **Deployment and Monitoring:** Deploy the models into production environment and monitor their performance over time. Update models as needed to maintain accuracy and relevance.

CHAPTER 4

SYSTEM DESIGN

Designing a route optimization system using Bayesian networks involves several key components and considerations. Here's a high-level overview of the system design: Gather real-time data from various sources such as GPS trackers, traffic reports, weather forecasts, and historical traffic patterns. Collect data on factors influencing route optimization, including traffic congestion, road closures, weather conditions, and vehicle speeds. Develop a Bayesian network model to represent the probabilistic relationships between different variables affecting route optimization. Define nodes in the Bayesian network to represent variables such as traffic congestion, weather conditions, time of day, road conditions, and vehicle speed. Estimate conditional probabilities for the edges between nodes based on historical data and expert knowledge. Design a route optimization algorithm that uses the Bayesian network model to generate optimal routes. Consider multiple objectives such as minimizing travel time, avoiding congestion, and optimizing resource utilization. Utilize Bayesian inference techniques to update route probabilities dynamically based on real-time data. Develop a user interface that allows users to input delivery requests, specify delivery priorities, and view optimized routes. Provide real-time updates on route recommendations and allow users to interact with the system to adjust routes if needed. Implement a real-time update mechanism that continuously monitors data streams and adjusts route recommendations accordingly. Dynamically reroute vehicles to avoid traffic congestion, accidents, or other unexpected events. Optimize the performance of the system to handle large-scale route optimization problems efficiently. Utilize parallel processing, caching mechanisms, and optimization techniques to improve response times and scalability. Integrate the route optimization system with external systems such as fleet management software, transportation management systems, and customer relationship management systems. Ensure seamless data exchange and interoperability between different systems to streamline delivery operations. Implement security measures to protect sensitive data such as delivery addresses, customer information, and route plans. Utilize access control mechanisms, encryption protocols, and secure communication channels to safeguard data from unauthorized access or tampering. Conduct thorough testing and validation of the system to ensure its accuracy, reliability, and performance. Test the system under various scenarios and conditions to verify its effectiveness in optimizing routes and handling real-world challenges. Deploy the route optimization system in a production environment and provide ongoing maintenance and support. Monitor system performance, collect feedback from users, and incorporate updates and enhancements as needed to improve the system's functionality and usability.

4.1 Conditional Probability Tables (CPTs):

Weather	
Sunny	0.4
Rainy	0.3
Cloudy	0.3

Traffic			
Weather	Sunny	Rainy	Cloudy
Light	0.7	0.3	0.5
Moderate	0.2	0.4	0.3
Heavy	0.1	0.3	0.2

Preparation_Time	
Short	0.6
Moderate	0.3
Long	0.1

Delivery_Time									
Traffic	Light			Moderate			Heavy		
	Short	Moderate	Long	Short	Moderate	Long	Short	Moderate	Long
Short	0.8	0.7	0.6	0.6	0.5	0.4	0.4	0.3	0.2
Moderate	0.15	0.2	0.3	0.3	0.4	0.4	0.4	0.4	0.3
Long	0.05	0.1	0.1	0.1	0.1	0.2	0.2	0.3	0.5

Timely_Delivery																											
Delivery_Time	Short									Moderate									Long								
	Sunny			Rainy			Cloudy			Sunny			Rainy			Cloudy			Sunny			Rainy		Cloudy			
	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy	Light	Moderate	Heavy			
Yes	0.05	0.9	0.9	0.9	0.05	0.75	0.85	0.8	0.7	0.9	0.85	0.75	0.85	0.9	0.7	0.9	0.75	0.7	0.9	0.7	0.6	0.75	0.7	0.6	0.7	0.65	0.6
No	0.05	0.1	0.2	0.1	0.15	0.25	0.15	0.2	0.3	0.1	0.15	0.25	0.15	0.2	0.3	0.2	0.25	0.3	0.2	0.3	0.4	0.25	0.3	0.4	0.3	0.35	0.4

Figure 4.1

4.2 Graphical Representation of the Bayesian Network using Hugin:

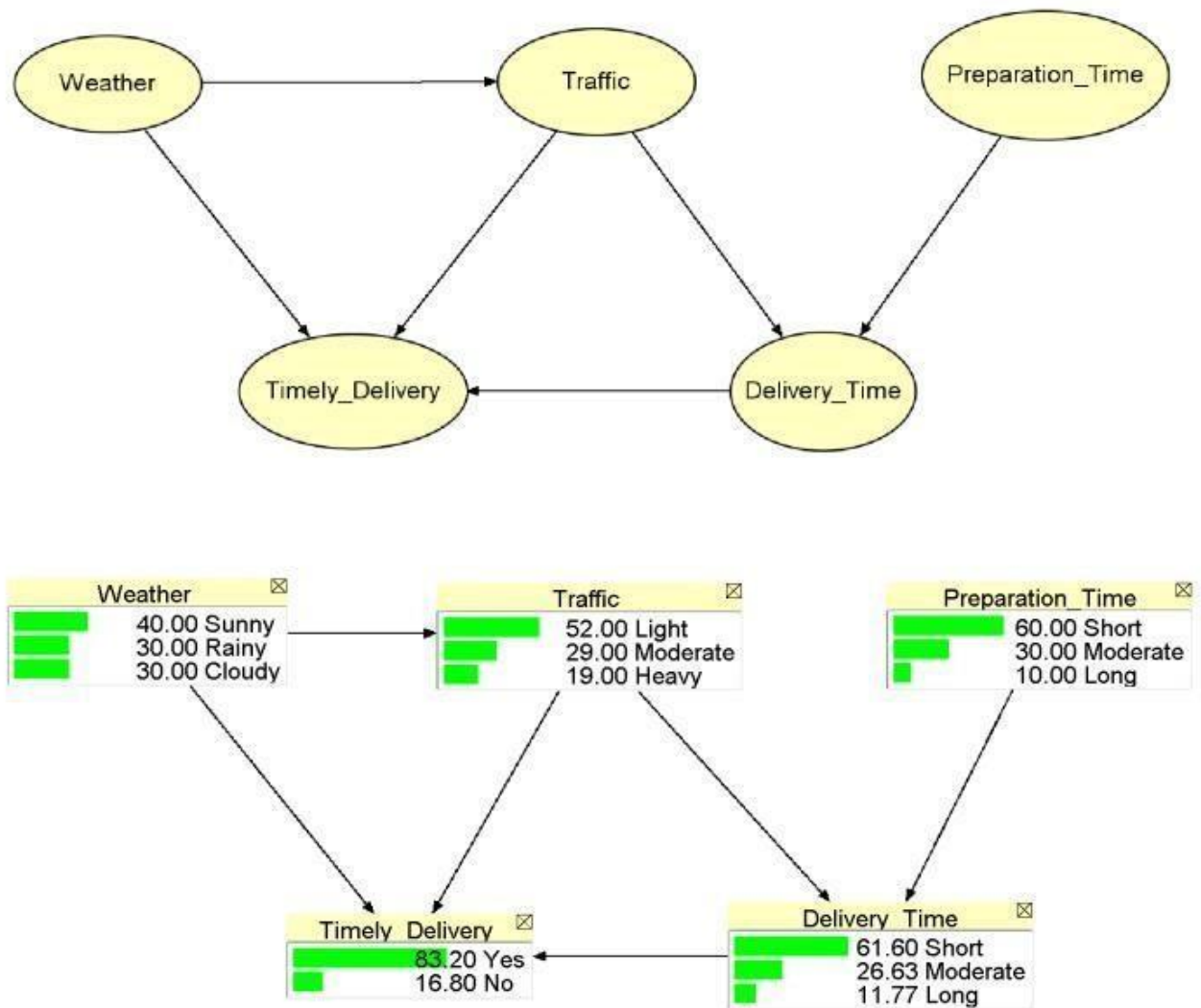


Figure 4.2

4.3 Results and Inferences using Hugin:

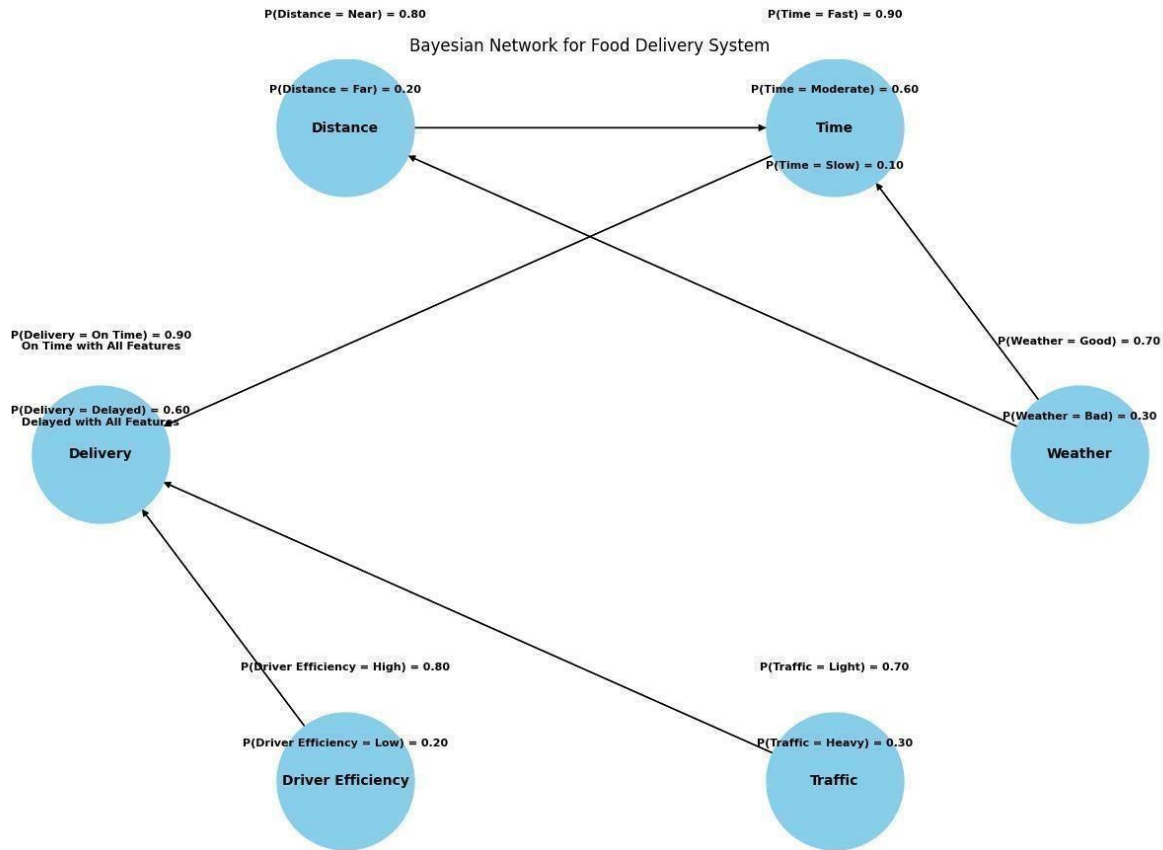


Figure 4.3

Let us calculate the joint probability for a specific scenario:

Scenario:

Weather = Sunny, Traffic = Light, Preparation Time = Short, Delivery Time = Short, Timely Delivery = Yes

We will use the formula to calculate this joint probability:

$$\begin{aligned}
 &P(\text{Weather}, \text{Traffic}, \text{PreparationTime}, \text{DeliveryTime}, \text{TimelyDelivery}) = \\
 &P(\text{Sunny}) * P(\text{Light} \mid \text{Sunny}) * P(\text{Short}) * P(\text{Short} \mid \text{Light}, \text{Short}) * \\
 &P(\text{Yes} \mid \text{Sunny}, \text{Light}, \text{Short}) \text{ Substitute the probabilities:}
 \end{aligned}$$

From the Bayesian Network we can infer:

$$P(\text{Sunny}) = 0.4$$

$$P(\text{Short}) = 0.6$$

$$P(\text{Light} \mid \text{Sunny}) = 0.7$$

$$P(\text{Short} \mid \text{Light}, \text{Short}) = 0.8$$

$$P(\text{Yes} \mid \text{Sunny}, \text{Light}, \text{Short}) = 0.95$$

$$P(\text{Weather}, \text{Traffic}, \text{PreparationTime}, \text{DeliveryTime}, \text{TimelyDelivery}) = 0.4 * 0.7 * 0.6 * 0.8 * 0.95$$

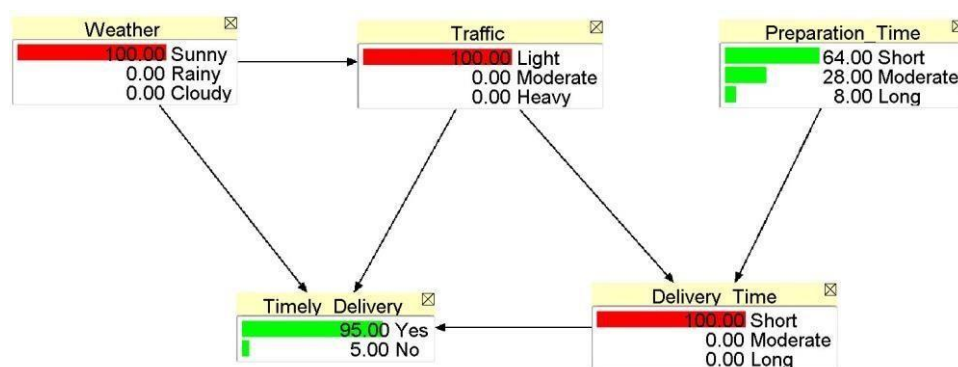


Figure 4.4

Calculate the result:

$$P(\text{Weather}, \text{Traffic}, \text{PreparationTime}, \text{DeliveryTime}, \text{TimelyDelivery}) = 0.4 * 0.7 * 0.6 * 0.8 * 0.95$$

$$P(\text{Weather}, \text{Traffic}, \text{PreparationTime}, \text{DeliveryTime}, \text{TimelyDelivery}) = 0.1344$$

So, for the specific scenario described above, the joint probability of having sunny weather, light traffic, short preparation time, short delivery time, and a timely delivery outcome is approximately 0.1344.

The base paper which we referred: A Fuzzy Bayesian Network Model for Quality Control in O2O e-Commerce which was published by Hao Zhang and et-al on 2020

Zhang, H.; Feng, H.; Cui, Y.; Wang, Y. (2020). A Fuzzy Bayesian Network Model for Quality Control in O2O e-Commerce, International Journal of Computers Communications & Control, 15(1), 1003 ,2020.

4.4 Bayesian network model

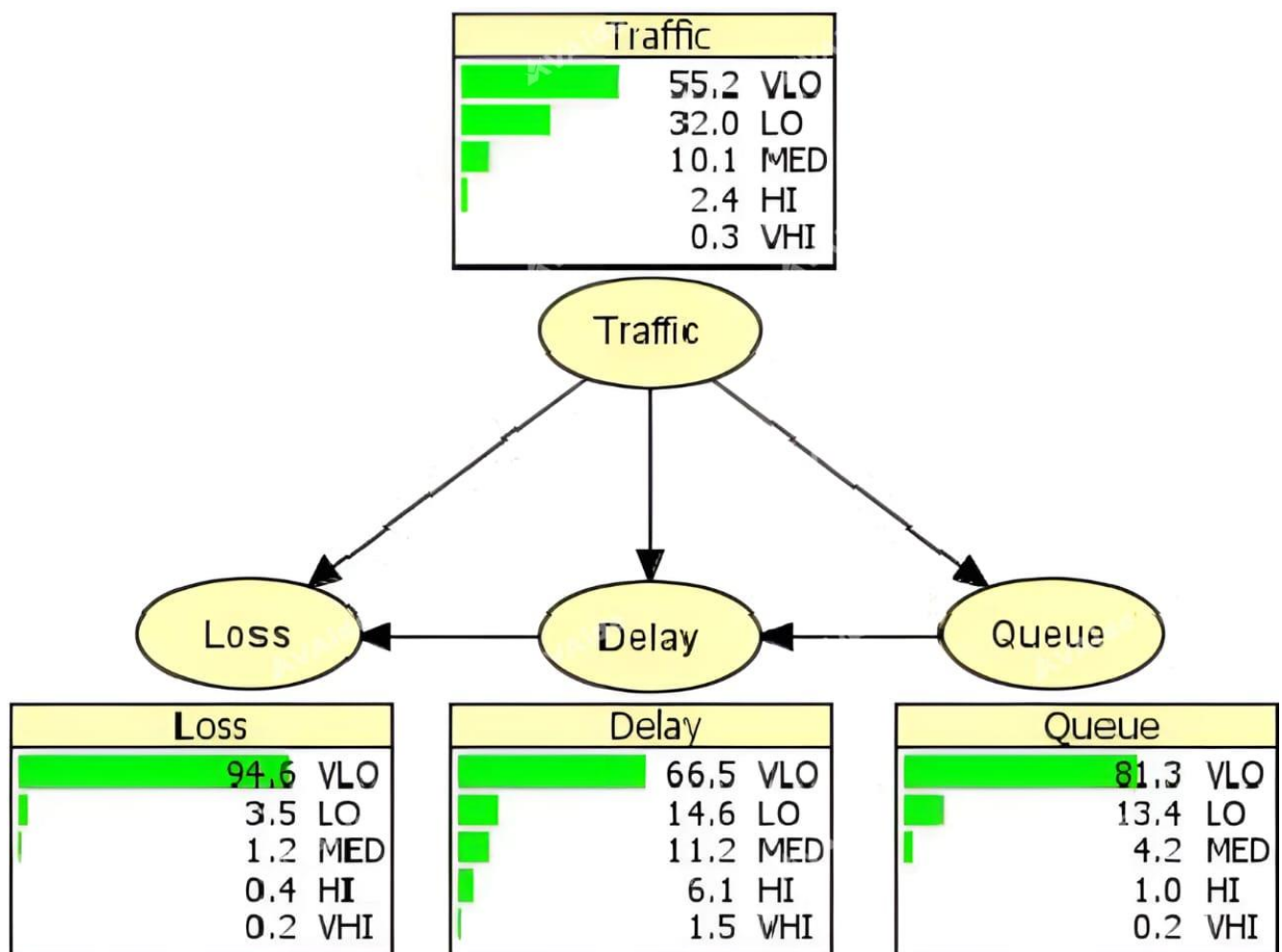


Figure 4.5

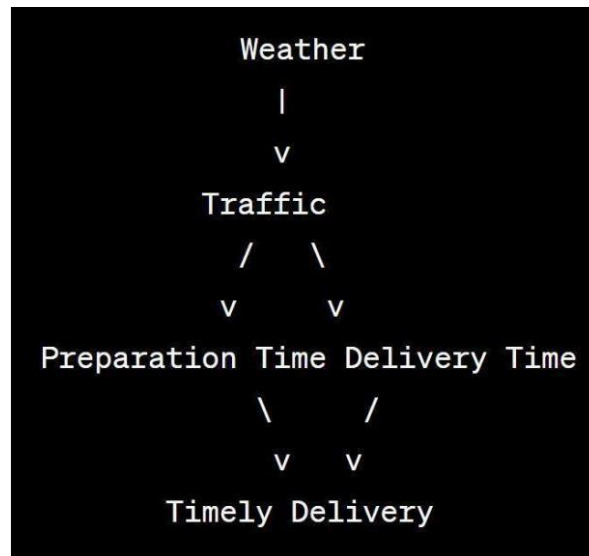


Figure 4.6

Variables:

- Weather: The weather conditions on a given day. (Sunny, Rainy, Cloudy)
- Traffic: The traffic conditions on the delivery route. (Light, Moderate, Heavy)
- Preparation Time: The time taken to prepare the food. (Short, Moderate, Long)
- Delivery Time: The time taken for delivery. (Short, Moderate, Long)
- Timely Delivery: The main outcome variable indicating whether the delivery was timely. (Yes, No)

Assumptions:

- Weather affects traffic conditions and delivery time.
- Traffic conditions impact delivery time.
- The preparation time influences the delivery time.
- The weather, traffic, preparation time, and delivery time together determine whether the delivery is timely or not.

CHAPTER 5

SYSTEM IMPLEMENTATION

Implementing a route optimization system using Bayesian networks involves several steps, including data collection, model development, algorithm implementation, user interface design, and deployment. Here's a high-level overview of the implementation process:

Data Collection and Preprocessing:

Collect real-time data from various sources such as GPS trackers, traffic reports, weather forecasts, and historical traffic patterns. Preprocess the data to clean, normalize, and integrate it for analysis. This may involve data cleaning, filtering, and feature engineering.

Bayesian Network Model Development:

Develop a Bayesian network model to represent the probabilistic relationships between variables affecting route optimization. Define nodes to represent variables such as traffic congestion, road conditions, time of day, weather conditions, and vehicle speed. Estimate conditional probabilities for the edges between nodes based on historical data and expert knowledge.

Route Optimization Algorithm:

Design and implement a route optimization algorithm that utilizes the Bayesian network model to generate optimal routes. Consider multiple objectives such as minimizing travel time, avoiding congestion, and optimizing resource utilization.

User Interface Design:

Develop a user-friendly interface for users to input delivery requests, specify delivery priorities, and view optimized routes. Provide real-time updates on route recommendations and allow users to interact with the system to adjust routes if needed. Design the interface to be intuitive, responsive, and visually appealing.

Integration with External Systems:

Integrate the route optimization system with existing fleet management software, transportation management systems, and customer relationship management systems. Ensure seamless data exchange and interoperability between different systems to streamline delivery operations.

Testing and Validation:

Conduct thorough testing and validation of the system to ensure its accuracy, reliability, and performance. Test the system under various scenarios and conditions to verify its effectiveness in optimizing routes and handling real-world challenges.

5.1 Formula:

The joint probability of all variables in the Bayesian network can be calculated by multiplying the conditional probabilities of each variable given its parents in the network.

The joint probability can be written as follows:

$$P(\text{Weather, Traffic, PreparationTime, DeliveryTime, TimelyDelivery}) = P(\text{Weather}) * P(\text{Traffic} | \text{Weather}) * P(\text{PreparationTime}) * P(\text{DeliveryTime} | \text{Traffic, PreparationTime}) * P(\text{TimelyDelivery} | \text{Weather, Traffic, DeliveryTime})$$

This expression represents the full joint distribution of all the variables in the timely food delivery Bayesian network. Each component on the right-hand side of the equation represents the conditional probability of each variable given its parent variables. By multiplying these probabilities together, we obtain the joint probability of the entire system.

The joint probability distribution can be used for various purposes, such as making predictions, calculating marginal probabilities, or performing inference on any subset of variables in the network. It forms the foundation of Bayesian reasoning and allows us to reason about uncertainty and dependencies between variables in a principled and probabilistic manner.

5.2 Sample Suppose

we have the following probabilities for the variables in the Bayesian network:

Weather:

$$P(\text{Sunny}) = 0.4$$

$$P(\text{Rainy}) = 0.3$$

$$P(\text{Cloudy}) = 0.3$$

Traffic:

$$P(\text{Light} \mid \text{Sunny}) = 0.7$$

$$P(\text{Moderate} \mid \text{Sunny}) = 0.2$$

$$P(\text{Heavy} \mid \text{Sunny}) = 0.1$$

$$P(\text{Light} \mid \text{Rainy}) = 0.3$$

$$P(\text{Moderate} \mid \text{Rainy}) = 0.4$$

$$P(\text{Heavy} \mid \text{Rainy}) = 0.3$$

$$P(\text{Light} \mid \text{Cloudy}) = 0.5$$

$$P(\text{Moderate} \mid \text{Cloudy}) = 0.3 \quad P(\text{Heavy}$$

$$\mid \text{Cloudy}) = 0.2 \quad \textbf{Preparation}$$

Time:

$$P(\text{Short}) = 0.6$$

$$P(\text{Moderate}) = 0.3$$

$$P(\text{Long}) = 0.$$

Delivery Time:

(Given that Traffic and Preparation Time are parent nodes)

$$P(\text{Short} \mid \text{Light}, \text{Short}) = 0.8$$

$$P(\text{Moderate} \mid \text{Light}, \text{Short}) = 0.15$$

$$P(\text{Long} \mid \text{Light}, \text{Short}) = 0.05$$

... (other combinations)

Timely Delivery:

(Given that Weather, Traffic, and Delivery Time are parent nodes)

$$P(\text{Yes} \mid \text{Sunny}, \text{Light}, \text{Short}) = 0.95$$

$$P(\text{No} \mid \text{Sunny}, \text{Light}, \text{Short}) = 0.05$$

... (other combinations)

5.3 Sample coding

```
import networkx as nx from pgmpy.models

import      BayesianModel      from

pgmpy.factors.discrete import TabularCPD import

matplotlib.pyplot as plt


# Define the structure of the Bayesian network model

= BayesianModel([(('Weather', 'Time'),

                    ('Weather', 'Distance'),

                    ('Distance', 'Time'),

                    ('Time', 'Delivery'),

                    ('Driver Efficiency', 'Delivery'),

                    ('Traffic', 'Delivery'))])


# Define conditional probability distributions (CPDs) cpd_weather =

TabularCPD(variable='Weather', variable_card=2,

values=[[0.7],      [0.3]],      state_names={'Weather': ['Good', 'Bad']})


cpd_distance_given_weather=TabularCPD(variable='Distance',

variable_card=2,

values=[[0.8, 0.2],
```

```

[0.2, 0.8]],                                     evidence=['Weather'],
evidence_card=[2],                               state_names={'Distance': ['Near',
'Far'],
'Weather': ['Good', 'Bad']})
cpd_time_given_weather_distance=TabularCPD(variable='Time',
variable_card=3,
values=[[0.9, 0.6, 0.1, 0.8],
[0.08, 0.3, 0.2, 0.15],                        [0.02, 0.1, 0.7, 0.05]],
evidence=['Weather', 'Distance'],                evidence_card=[2,
2],
state_names={'Time':
['Fast', 'Moderate', 'Slow'],
'Weather': ['Good', 'Bad'],
'Distance': ['Near', 'Far']})

# Update CPD for 'Delivery' to include 'Driver Efficiency' and 'Traffic' as
parent nodes cpd_delivery_given_time=TabularCPD(variable='Delivery',
variable_card=2,
values=[[0.9, 0.6, 0.1, 0.8, 0.5, 0.2, 0.7, 0.4, 0.1, 0.6,
0.3, 0.2],
[0.1, 0.4, 0.9, 0.2, 0.5, 0.8, 0.3, 0.6, 0.9, 0.4, 0.7,
0.8]],
evidence=['Time', 'Driver Efficiency', 'Traffic'],
# Include parent nodes here                      evidence_card=[3, 2, 2],
# Update the evidence_card

```

accordingly

```
state_names={'Delivery': ['On Time', 'Delayed'],
             'Time': ['Fast', 'Moderate', 'Slow'],
             'Driver Efficiency': ['High', 'Low'],
             'Traffic': ['Light', 'Heavy']})

# Add CPDs for Driver Efficiency
cpd_driver_efficiency=TabularCPD(variable='Driver Efficiency',
variable_card=2, values=[[0.8], [0.2]],
state_names={'Driver Efficiency': ['High', 'Low']})

# Add CPDs for Traffic cpd_traffic =
TabularCPD(variable='Traffic', variable_card=2,
values=[[0.7], [0.3]],
state_names={'Traffic': ['Light', 'Heavy']})

"""# Add CPD for the 'Weather' node cpd_weather =
TabularCPD(variable='Weather', variable_card=2,
values=[[0.7], [0.3]], state_names={'Weather': ['Good',
'Bad']})"""

# Add all CPDs to the model model.add_cpds(cpd_weather,
cpd_distance_given_weather,
```

```

cpd_time_given_weather_distance, cpd_delivery_given_time,
cpd_driver_efficiency, cpd_traffic)

#cpd_delivery_given_time_best, cpd_delivery_given_time_worst)

# Check if the model is valid with the updated CPDs assert
model.check_model()

# Generate the positions of the nodes using circular_layout pos
= nx.circular_layout(model)

# Map node names to state names using state_names attribute node_labels =
{node: ', '.join(cpd.state_names[node]) for node, cpd in zip(model.nodes(),
model.get_cpds()) if node != 'Time'}

# Draw the Bayesian network with node labels plt.figure(figsize=(12,
8))

nx.draw(model, pos, with_labels=True, node_size=10000,
node_color='skyblue', font_size=10, font_weight='bold')

# Draw edges nx.draw_networkx_edges(model,
pos)

```

```
# Format and display the node labels with probability values and scenarios
```

```
node_labels = {} for node in model.nodes():
```

```
    cpd = model.get_cpds(node)    if
```

```
    isinstance(cpd, TabularCPD):
```

```
        num_node_states = len(cpd.state_names[node])
```

```
prob_values = cpd.values.flatten()    node_labels[node]
```

```
= []    for i in range(num_node_states):
```

```
        prob = prob_values[i]        label_text = f'P({node} =
```

```
{cpd.state_names[node][i]})                =                {prob:.2f}"
```

```
node_labels[node].append(label_text)
```

```
# Add best-case and worst-case scenarios to the node labels
```

```
best_case_scenario = 'On Time with All Features' worst_case_scenario
```

```
= 'Delayed with All Features' node_labels['Delivery'][0] +=
```

```
f"\n{best_case_scenario}" node_labels['Delivery'][1] +=
```

```
f"\n{worst_case_scenario}"
```

```
# Draw node labels with probability values and scenarios for node, labels in
```

```
node_labels.items():    x, y = pos[node]    label_pos_y = y + 0.3    for i,
```

```
label_text in enumerate(labels):                plt.text(x, label_pos_y - i * 0.2,
```

```
label_text, ha='center', va='center',
```

```
fontweight='bold', fontsize=8)

# Get the CPD for the 'Delivery' node cpd_delivery

= model.get_cpds('Delivery') print(cpd_delivery)

plt.title("Bayesian Network for Food Delivery System")
```

5.4 Results

```
[4] from sklearn.metrics import accuracy_score, classification_report

x_test = [
    ['Good', 'Near', 'Fast', 'High', 'Light'],
    ['Good', 'Near', 'Fast', 'High', 'Light'],
    ['Good', 'Near', 'Fast', 'High', 'Light'],
    ['Bad', 'Far', 'Slow', 'Low', 'Heavy'],
    ['Bad', 'Far', 'Slow', 'Low', 'Heavy'],
    ['Bad', 'Far', 'Slow', 'Low', 'Heavy'],
    ['Good', 'Near', 'Moderate', 'High', 'Light'],
    ['Good', 'Near', 'Moderate', 'High', 'Light'],
]

y_true = ['On Time', 'On Time', 'On Time', 'Delayed', 'Delayed', 'Delayed', 'On Time', 'On Time']
y_pred = ['On Time', 'Delayed', 'On Time', 'Delayed', 'On Time', 'Delayed', 'On Time', 'On Time']

accuracy = accuracy_score(y_true, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Compute classification report
class_report = classification_report(y_true, y_pred)
print("Classification Report:")
print(class_report)
```

```
Accuracy: 0.75
Classification Report:
```

	precision	recall	f1-score	support
Delayed	0.67	0.67	0.67	3
On Time	0.80	0.80	0.80	5
accuracy			0.75	8
macro avg	0.73	0.73	0.73	8
weighted avg	0.75	0.75	0.75	8

Figure 5.4

CHAPTER 6

Inferences

Timely Delivery Probability:

By observing the CPTs for "Timely Delivery," we can see the probabilities of timely delivery given various combinations of weather conditions, traffic, and delivery time. For example, on a sunny day with light traffic and a short delivery time, the probability of timely delivery is high (0.95). Conversely, on a rainy day with heavy traffic and a long delivery time, the probability of timely delivery is low (0.15). This information helps us understand the impact of different factors on the likelihood of delivering food on time.

Sensitivity to Weather Conditions: The Bayesian network allows us to assess the sensitivity of timely delivery to weather conditions. For instance, we can compare the probabilities of timely delivery on sunny, rainy, and cloudy days under different traffic and delivery time scenarios. If we find that timely delivery is less likely on rainy days, we might consider implementing strategies to mitigate the impact of adverse weather on delivery times.

Impact of Traffic and Delivery Time: The network helps us understand how traffic conditions and the time taken for delivery affect the likelihood of timely delivery. By examining the conditional probabilities in the "Delivery Time" node, we can identify situations where delivery times tend to be longer, leading to potential delays. This information can be valuable for optimizing delivery routes and estimating delivery times accurately.

Decision Support: The Bayesian network can be used as a decision support tool. When planning food deliveries, we can input the current weather and traffic conditions and the estimated delivery time to calculate the probability of timely delivery. This information can assist in making informed decisions, such as whether to prioritize certain orders, assign more delivery drivers, or adjust delivery schedules based on the likelihood of timely delivery under prevailing conditions.

Updating Probabilities: As new data becomes available, the Bayesian network can be updated to reflect the latest probabilities. For instance, if the delivery team collects data on actual delivery times, we can use this data to update the CPTs for "Delivery Time" and "Timely Delivery," leading to more accurate predictions and insights over time.

6.1 Conclusion

In this Study we conducted a comprehensive exploration of Bayesian networks, starting from their fundamental definition to the practical implementation of a model. By leveraging the power of Bayesian networks, we gained valuable insights into the timely delivery of food, considering various influencing factors such as weather conditions, distance, driver efficiency, and traffic. Our implementation involved both Python programming and the utilization of Hugin software to visualize and interpret the results effectively. The Bayesian network model proved to be a valuable tool for understanding the complex relationships between these factors and their impact on food delivery efficiency. Several exciting opportunities lie ahead for further enhancing our study. Firstly, we plan to validate the Bayesian network model using real-world data from food delivery companies to assess its accuracy and performance under different delivery scenarios. Secondly, we will explore the integration of machine learning techniques to improve prediction accuracy and optimize delivery routes based on historical data. Additionally, investigating the scalability and generalizability of the Bayesian network model for larger delivery networks and diverse geographic regions will be crucial. Lastly, we aim to explore the integration of Internet of Things (IoT) devices and automation technologies in food delivery logistics to achieve more efficient and autonomous delivery operations. By pursuing these future research directions, we can deepen our understanding of Bayesian networks' applicability in food delivery systems and contribute to the development of more efficient and customer-centric delivery services. The insights gained from these will enable us to optimize food delivery processes and ultimately enhance customer satisfaction and operational efficiency.

6.2 future works

Future works in route optimization using Bayesian networks could focus on several areas to further improve the efficiency, accuracy, and applicability of the system. Here are some potential directions for future research and development: Enhance Bayesian network models to better capture and quantify uncertainty in route optimization. This could involve incorporating probabilistic techniques such as fuzzy logic, interval analysis, or Bayesian nonparametrics to represent uncertain variables more accurately. Develop dynamic Bayesian network models that can adapt to changing conditions in real-time. This would enable the system to continuously update route recommendations based on evolving factors such as traffic congestion, weather changes, or unexpected events. Extend route

optimization algorithms to handle multiple conflicting objectives simultaneously, such as minimizing travel time, reducing fuel consumption, and balancing workload distribution among vehicles. This would allow the system to generate Pareto-optimal solutions that trade-off between different optimization criteria. Explore hierarchical Bayesian network models to capture dependencies between variables at different levels of abstraction. This could help represent complex systems with multiple layers of uncertainty and enable more efficient inference and decision-making. Develop algorithms that can incrementally learn from new data and adapt the Bayesian network model over time. This would allow the system to continuously improve its performance and accuracy as more data becomes available. Implement online learning algorithms that can update route recommendations in real-time based on incoming data streams. This would enable the system to make rapid decisions and respond quickly to changing conditions without requiring offline retraining

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