The Asian Review of Civil Engineering
ISSN: 2249-6203 (P); 2583-7893 (E)
Vol.13 No.1, 2024, pp.44-52

www.crijournals.org
DOI: https://doi.org/10.70112/tarce-2024.13.1.4230

The Traffic Monitoring Decision Support Tool: A Web-Based Decision Support Tool for Enhanced Traffic Data Collection, Analysis, and Estimation

Abdulkadir Ozden[1] and Ardeshir Faghri[2]
[1]Department of Civil Engineering, Sakarya University of Applied Sciences, Sakarya, Türkiye
[2]Department of Civil and Environmental Engineering, University of Delaware, Newark, United States
E-mail: aozden@subu.edu.tr, faghri@udel.edu
(Received 5 March 2024; Revised 12 April 2024; Accepted 16 April 2024; Available online 24 April 2024)

Abstract - **Accurate collection and analysis of traffic data are essential for effective transportation planning and management. The Traffic Monitoring Decision Support Tool (TMDEST) is an innovative web-based expert system designed to enhance the capabilities of transportation professionals in traffic data collection, analysis, and reporting. TMDEST integrates federal guidelines, established research methods, and state-specific information into a comprehensive knowledge base. The system comprises multiple core modules, including the MADT/AADT Methods Module, the TPG Methods Module, and the Adjustment Factors Module. Each module addresses distinct aspects of traffic monitoring, providing intuitive interfaces for user data input and generating tailored recommendations. The MADT/AADT Methods Module improves the estimation of Monthly Average Daily Traffic (MADT) and Annual Average Daily Traffic (AADT) through three methods: Simple Average, AASHTO, and HPSJB, each evaluated based on complexity and data completeness. The TPG Methods Module uses clustering techniques to form Traffic Pattern Groups (TPGs), enhancing the accuracy of short-duration count data. The Adjustment Factors Module helps determine the necessary adjustment factors for precise AADT and MADT estimations. TMDEST's validation, verification, and evaluation processes ensure reliability by checking for completeness, consistency, and correctness. Its web-based design facilitates easy access and updates, making it an invaluable tool for transportation agencies. Future enhancements include an online feedback system to continuously improve TMDEST's functionality and user experience.**
Keywords: **Traffic Monitoring, Knowledge-Based Systems, Traffic Data Collection, Traffic Pattern Groups, Decision Support Tool**

I. INTRODUCTION

Traffic monitoring is a critical process that involves collecting and analyzing data on roadway usage and performance, including metrics such as traffic volume, vehicle classification, truck weights, speed, and average travel time. This data is fundamental for making informed transportation decisions, enhancing roadway mobility, and ensuring effective planning and operational activities [1], [2].

The goal of traffic monitoring programs is to achieve comprehensive and continuous data collection on all roadway segments year-round. However, technological and financial constraints make this impractical. Therefore, it is essential to gather statistically significant and accurate data that is representative of the study area by grouping roadways with similar traffic patterns (Traffic Pattern Groups - TPGs) and using continuous count stations, such as Automated Traffic Recorders (ATRs) and traffic cameras, to generate correction factors. This approach enables the extrapolation of short-duration counts to annual averages, balancing continuous and short-duration count programs for reliable and cost-effective traffic data collection [3], [4].

Accurate estimation of Annual Average Daily Traffic (AADT) and its variations, such as Annual Average Daily Truck Traffic (AADTT), Annual Average Weekday Traffic (AAWT), and Monthly Average Daily Traffic (MADT), is vital for numerous planning and operational decisions. The proper establishment of TPGs is crucial for accurate AADT estimation, employing methods like cluster analysis, regression, and artificial neural networks (ANN). The sample size and location of continuous count stations, along with the selection of appropriate methods to form TPGs and derive correction factors, require careful consideration [5].

A. AADT Estimation and Traffic Pattern Groups in Traffic Monitoring Programs

Transportation agencies utilize two primary data collection programs: continuous and short-duration. Continuous data programs involve sensors placed in or near the pavement for ongoing monitoring of traffic measures like volume, vehicle classification, and speed. Traditionally, ATRs which have been used require traffic disruption to install and maintain and are not cost-effective. Recent advancements, such as microwave radar sensors and image processing from cameras, have mitigated these issues [1], [6].

Short-duration data programs provide spatial coverage by collecting data over 3-7 days on segments with significant traffic characteristic changes. These counts, performed periodically, help update AADT and its variations (MADT, AADTT). Adjustment factors derived from continuous data normalize short-duration counts to estimate AADTs, considering the temporal variations [5], [7].

Establishing Traffic Pattern Groups (TPGs) is crucial for grouping roadways with similar traffic patterns, facilitating accurate AADT estimation. Methods like cluster analysis, regression, and artificial neural networks (ANN) have been used to refine TPG formation, addressing sampling errors and improving reliability [3], [4], [8].

The primary errors in AADT estimation include sampling errors, errors in TPG establishment, and incorrect road assignments [7]. FHWA [5] and previous studies identified challenges such as evolving traffic trends affecting group consistency and the need for clear group definitions [3]. Various clustering methods have been evaluated, including least squares, agglomerative hierarchical clustering, and k-means [3], [9], [10], [11].

Bassan [2] developed a statistical approach for TPG determination using volume, seasonal variation, and land use characteristics, applicable to other states. Subsequently, a project with DelDOT improved TPG development using hierarchical cluster analysis [12]. The complexity of these methods led to the development of a Knowledge-Based Expert System (KBES), called TMDEST, to facilitate TPG evaluation without requiring advanced statistical methods.

B. Knowledge-Based Expert Systems

Expert systems (ES) are computer systems that mimic the cognitive skills of human experts to assist users in complex decision-making processes [13]. Knowledge-based expert systems (KBES) can make inferences and provide explanations, distinguishing them from conventional programs. They dynamically ask relevant questions and derive precise conclusions, performing “reasoning over representation on human knowledge” [13].

ES offer advantages over human experts, such as availability, speed, consistency, and the ability to operate in hazardous environments. However, they also have limitations, including the difficulty of knowledge acquisition, development time and cost, and user trust issues [13], [14].

KBES can range from simple selection-aid tools to complex systems requiring professional development. They are widely used in fields like medical diagnostics and customer service. Early applications date back to the 1960s, gaining traction in the 1980s and expanding with the Internet’s proliferation in the 1990s [15], [16]. In transportation, ES applications have been developed for planning, safety, work zone management, pavement management, fuel efficiency, and policy [4], [17], [18], [19], [20], [21], [22], [23], [24].

A KBES consists of three main components: the knowledge base, inference engine, and user interface (Figure 1). The knowledge base contains all relevant knowledge, the inference engine applies rules to reach conclusions, and the user interface interacts with users. Verification, Validation, and Evaluation (VVE) are critical tasks in KBES development to ensure the system’s accuracy and usefulness [25], [26].

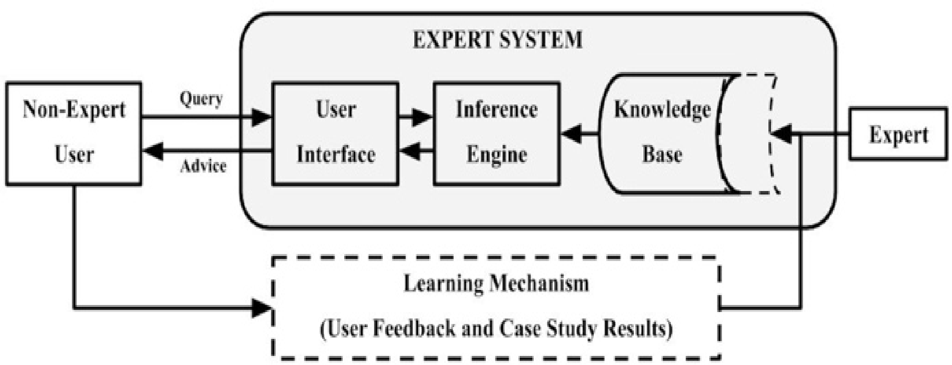

Fig. 1 Typical architecture of an expert system

On the other hand, web-based expert systems have become more prevalent, enhancing accessibility and development efficiency. These systems allow non-AI experts to develop simple expert systems, facilitating data processing and decision-making [27], [28].

This study presents an expert system-based decision support tool (TMDEST) aimed at enhancing traffic monitoring programs. The primary objectives of TMDEST are:

1. To evaluate various methods for AADT/MADT estimation and TPG establishment based on criteria such as data availability, extent of missing data, temporal variations, and seasonality.
2. To assist in forming TPGs using an approximate approach.
3. To guide the selection and application of appropriate adjustment factors.

TMDEST is primarily designed for transportation agencies responsible for traffic data collection, analysis, and reporting, but it can also be utilized by researchers and professionals interested in traffic data and TPGs.

II. METHODOLOGY

This study presents the development and evaluation of the TMDEST, a web-based expert system designed to enhance the decision-making capabilities of transportation professionals. The methods section outlines the systematic approach used in the design, implementation, and validation of TMDEST.

A. System Design and Architecture

TMDEST was conceptualized as a web-based expert system to ensure accessibility and ease of use. The system comprises two main components: an informative tool and an interactive tool. The informative tool provides user-requested information through a rule-based system where users select on-screen options to receive recommendations. The interactive tool allows users to input data and make analytical conclusions, enhancing the system's functionality.

The system architecture is built around three core modules: MADT/AADT Methods Module, TPG Methods Module, and Adjustment Factors Module. Each module is designed to address specific aspects of traffic monitoring and data analysis. The modules are integrated into a single platform to provide comprehensive support for transportation agencies.

B. Module Development

1. MADT/AADT Methods Module: This module focuses on improving the estimation of Monthly Average Daily Traffic (MADT) and Annual Average Daily Traffic (AADT). Three methods were included: The Simple Average method, the AASHTO method, and the HPSJB method [29], [30], [31], [32]. Each method was evaluated based on processing complexity and data completeness. Scores were assigned to each method based on user inputs, and the final recommendation was generated using a logic block.

2. TPG Methods Module: The Traffic Pattern Group (TPG) Methods Module helps create statistically sound groups for deriving adjustment factors and summary statistics for short-duration counts. Four methods were included: the traditional approach, cluster analysis, cluster analysis with functional classification, and volume-based grouping. Each method was evaluated based on seasonal variation, volume trends, and geographic coverage. The logic blocks in this module used backward chaining to minimize node complexity and ensure efficient processing.

3. Adjustment Factors Module: This module assists in determining the necessary adjustment factors for accurate MADT and AADT estimations. Users input data regarding the duration, format, and timing of short-duration counts. The inference engine then selects appropriate adjustment factors and provides explanations to the user. The module does not calculate adjustment factors directly but enhances the accuracy of existing estimations by guiding users through the selection process.

C. Data Collection and User Input

TMDEST requires user input to function effectively. Data inputs include the number of TPGs, continuous count stations (CCS), and coefficient of variation (CV) values for selected TPGs. Users also choose desired confidence levels and precision intervals. The system guides users through the data input process with on-screen instructions, simple explanations, examples, and external links as needed.

D. Validation, Verification, and Evaluation

The validation, verification, and evaluation (VVE) process is crucial to ensure the reliability and usefulness of TMDEST. The VVE process was conducted in several stages:

1. Purpose and Requirements Evaluation: The system's purpose and requirements were assessed to ensure each module collected the necessary data and produced satisfactory results.

2. Completeness Check: All rules in a logical path were checked to ensure they produced conclusions.

3. Consistency Check: Each module was checked for mutually inconsistent conclusions within the rules.

4. Correctness Evaluation: Each module was evaluated to ensure it met its initial goals and specifications.

5. Knowledge Base Validation: The knowledge base was validated using published documents and expert knowledge. A True/False test was used to ensure the consistency and accuracy of the knowledge base.

E. Implementation

TMDEST was implemented using a web-based platform to maximize accessibility. The system was developed in collaboration with transportation professionals to ensure it met the practical needs of its users. The modular design allows for easy updates and refinements based on user feedback.

III. DEVELOPMENT OF TRAFFIC MONITORING DECISION SUPPORT TOOL (TMDEST)

The Traffic Monitoring Decision Support Tool (TMDEST) was developed to address the growing needs of transportation professionals tasked with managing and analyzing traffic data. Recognizing the challenges associated with current traffic monitoring methods, TMDEST aims to provide a more streamlined and user-friendly approach. This tool integrates both rule-based and data-driven methodologies to enhance the accuracy and efficiency of traffic data analysis. TMDEST features two primary sections: an informative tool that delivers pre-processed information based on user queries and an interactive tool that facilitates dynamic data entry and analysis. The informative tool is designed to simplify the decision-making process by offering straightforward recommendations, while the interactive tool supports complex analytical tasks, allowing users to input various data points and receive tailored outputs.

A. MADT/AADT Methods Module

Estimation of MADT and AADT measures are two of the critical tasks in the traffic monitoring program. The aim of the module is to improve the decision of evaluating and selecting the proper MADT/AADT estimation methods. Among many approaches developed and used over the years, three methods are included based on the complexity of the calculations, and the amount and spread of the missing data from continuous count stations.

Among these three methods, the Simple Average method is chosen for its simplicity, while the AASHTO method is widely used by highway agencies due to its incorporation of temporal variations. Research has shown that the AASHTO method performs comparably to other methods that consider temporal variations [30], [31], [32]. The HPSJB method, a recent development, improves estimation accuracy by accounting for hourly missing data [29]. Each method is given a score between 0 and 300 (either 0, 100, 200 or 300) based on selected criteria such as complexity level of the processing, the presence of missing data, and the amount of missing data. These criteria will be prompted to the user to assign a score to each method based on how well they meet the criteria (well, moderate, poor). Table I presents the scores assigned to each method based on the user's responses.

The Simple Average and HPSJB methods represent the least and most complex methods, respectively, while the AASHTO method incorporates temporal variation but excludes hourly missing data. Agencies can replace the AASHTO method with other methods using day-of-week and monthly adjustment factors to see how well they fit in the recommended methods list. Key variables in this module include *Have_missing, Amount_missing, Dist_of_missing, Missing_hourly, Temporal_variation, Simple_Average, AASHTO,* and *HPSJB.* The *Note* variable displays specific information based on user selections. For example, if the data distribution is not random, a note will explain potential causes like heavy volume or poor maintenance, and suggest monitoring to improve data accuracy and reliability.

TABLE I SCORE TABLE FOR MADT/AADT ESTIMATION METHODS

Evaluation Criteria		Simple Average	AASHTO	HPSJB
Level of Processing		300	200	100
Have Missing Data	Yes	*Included in the following criteria		
	No	300	300	300
Amount of Missing Data (days/month)	≤ 3 days	200	300	300
	≤ 7 days	100	300	300
	≤ 15 days	0	300	300
	≥ 15 days	0	300	300
Hourly Missing Data	Yes	0	0	300
	No	300	300	300
Temporal Variation	Yes	0	300	300
	No	300	0	0

The module's rules are constructed in a single logic block, focusing on evaluating the presence, distribution, and amount of missing data and assigning scores to the three methods. The command block begins with a welcome page that explains the module's purpose, evaluation procedure, and possible MADT/AADT estimation methods. This page is shown at the start of the module, before prompting the user with questions. The command block uses forward chaining to derive confidence and collection variables, then presents necessary information, including the user's answers, a sorted list of estimation methods, and relevant notes. Figures 2 illustrates the logic block of the TMDEST.

B. TPG Methods Module

The Traffic Pattern Group (TPG) Methods Module helps create statistically sound groups for deriving adjustment factors and summary statistics for short-duration counts. This module includes four methods: the traditional approach, cluster analysis, cluster analysis with functional classification, and volume-based grouping. These methods are evaluated based on seasonal variation, volume trends, and geographic coverage, and assigned scores (0 to 300) based on user responses (Table II). The scores are then totaled to provide a final recommendation.

The module's main objective is to quickly evaluate different TPG methods, allowing users to establish TPGs, which require extensive data and statistical procedures. Logic blocks set rules for these variables, and a backward chaining method reduces node complexity. The "Seasonal Variation" logic block asks about the inclusion and extent of seasonal variation, while the "Functional Classification" logic block evaluates the use of roadway functional classification in TPG establishment. The command block, similar to the MADT/AADT Estimation Module, begins with a welcome page explaining the module's purpose and TPG methods. After deriving collection and confidence variables, it displays recommended TPG methods and informative notes explaining the decisions.

TABLE II SCORE TABLE FOR TPG ANALYSIS METHODS

Evaluation Criteria		Trad. Appr.	Cluster Anlys.	Cluster with Roadway Funct. Class.	Volume Groups
Level of Processing		300	100	100	200
Seasonal Variation	Yes	0	300	300	0
	No	300	200	200	300
Seasonal Variation in Same Urban/Rural Typology	Yes	0	300	300	0
	No	0	0	0	0
Functional Classification	Yes	300	100	300	100
	No	0	0	0	0

C. Approximate TPG Groups Module

This module allows users to establish traffic pattern groups using an approximate clustering method, ideal for quickly evaluating current groups with recent data. It begins with questions on seasonal variation and urban/rural typology for each roadway functional class to determine the necessary number of groups. The module follows FHWA's roadway functional classification categories [5] and HPMS data reporting categories, including:

1. Interstates, Freeways & Expressways
2. Other Principal Arterials
3. Minor Arterials
4. Collectors
5. Local Roads

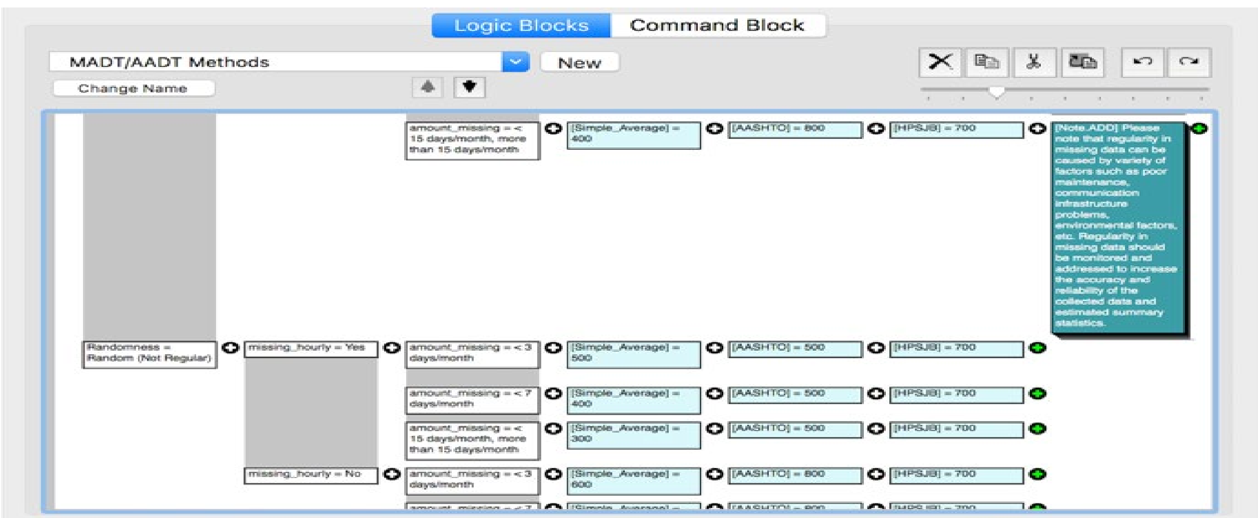

Fig. 2 Logic block of MADT/AADT estimation module

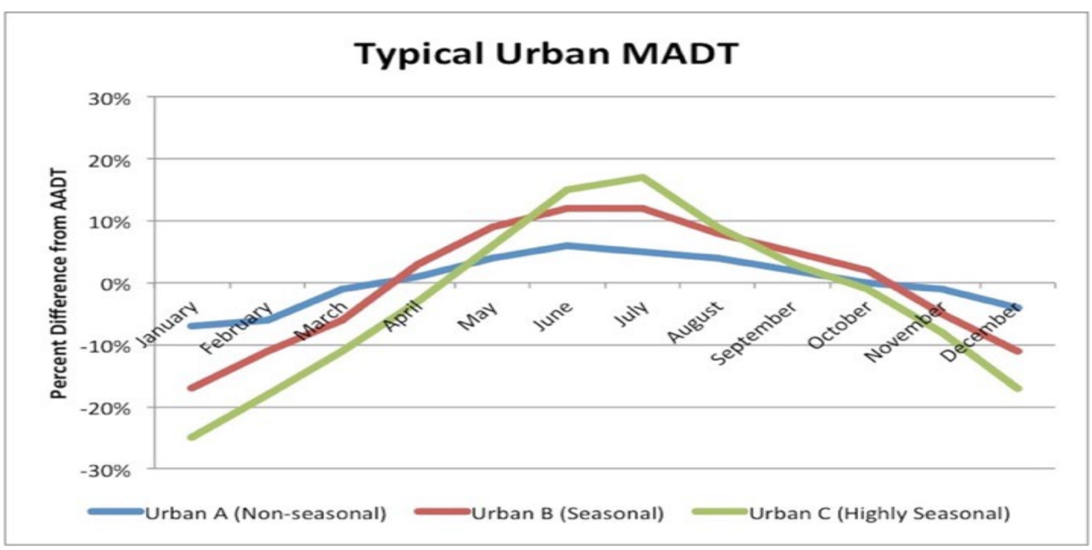

Fig. 3 Typical Urban MADTs

Seasonal variation and functional classification help identify groups. Users are asked about seasonality for each class, representing a simplified version of the cluster analysis with functional classification method. Based on responses, the module assesses whether multiple groups are needed for each class and evaluates opportunities to merge groups across different functional classifications if similar seasonality is present. A graphical representation of seasonality trends, showing MADT trends as a percentage difference from AADT for various road types, is provided to users to enhance the understanding (Figure 3 and Figure 4).

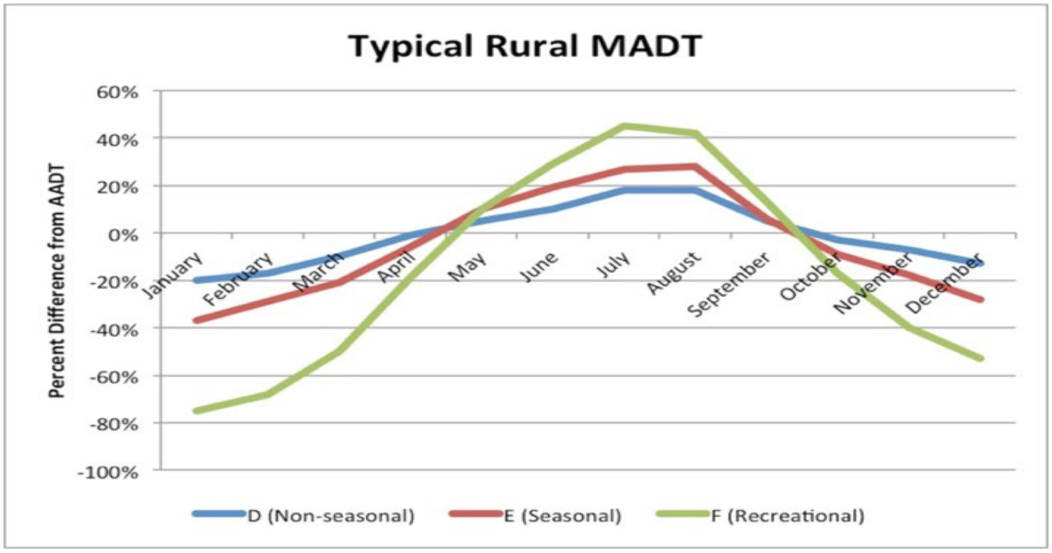

Fig. 4 Typical Rural MADTs

This module uses 19 logic blocks to determine the presence and extent of seasonality in functional classes. Rules are fired only when necessary, minimizing irrelevant questions (i.e., if the user did not indicate seasonality in a specific functional class, there is no need to ask about the extent of the seasonality). The inference engine checks for similar seasonality across classes using Boolean expressions to identify potential group mergers. However, certain classes, like seasonal interstates, are not grouped with others, like seasonal minor collectors. The command block guides users through the module, explaining the approximate method and presenting the recommended TPGs with additional notes if needed. At the end, the command block presents the list of TPGs that are recommended with additional notes if necessary, specifically emphasizing the purpose of the module and approximation of the recommended groups.

D. Adjustment Factors Module

The Adjustment Factors Module improves the estimation of MADT and AADT values from short-duration data. It helps quickly check if current volume data produce reasonable AADT estimates and determines necessary adjustment factors for accurate AADTs. Improper adjustment factors can lead to overestimation or underestimation of summary statistics. Users are asked specific questions about when, how long, and in what format the short-duration data was collected. The inference engine selects and presents the appropriate adjustment factors with explanations. The module evaluates various aspects like vehicle or axle type, data collection duration, year, month, and specific days. For example, users might be prompted to use axle correction factors, monthly adjustment factors for February, and growth factors for specific years, along with explanatory notes.

The module does not calculate adjustment factors, as this requires extensive data and calculations using continuous count stations, which most agencies already handle. Instead, it aims to enhance the accuracy of these estimations.

The command and logic blocks are structured similarly to previous modules. Questions are presented in a logical order with necessary explanations to derive list, collection, and confidence variables. The inference engine then summarizes user selections and recommended adjustment factors for AADT estimation based on the user's inputs.

E. Sample Size Estimation Module

The Sample Size Estimation Module differs from previous modules by requiring user data input, such as the number of TPGs, continuous count stations (CCS), and coefficient of variation (CV) values for selected TPGs. Users also choose desired confidence levels (90%, 95%, or 99%) and precision intervals through multiple-choice selections.

Users are guided with on-screen instructions to input data. Simple explanations, examples, and external links are provided if needed. The number of TPGs is restricted to integers between 2 and 20, and the number of CCS to integers between 1 and 100, to manage processing time.

For CV determination, users select whether they have true CV values, prefer to derive values using Excel, or use an approximate graphical method. If CV values are unknown, an approximate method is provided using MADT graphs to assess seasonality. Users answer simple questions, such as “Does traffic volume nearly double in summer months?” to assign approximate CV values.

The numeric variables, confidence levels, and precision intervals are used to calculate t-statistics and precision levels. The module calculates the required minimum sample size based on current CCS, CV values, and selected confidence levels and precision intervals.

F. Validation, Verification and Evaluation (VVE)

Validation, verification, and evaluation (VVE) are crucial to ensure the reliability and usefulness of an expert system. Miskell *et al.,* (1989) describe these tasks as:

1. *Verification:* Ensuring the system is built correctly.
2. *Validation:* Ensuring the right system is built.
3. *Evaluation:* Assessing the system’s usefulness.

The size and complexity of an expert system determine the VVE methods used. Wentworth et al. [26] recommend methods suitable for transportation studies. TMDEST uses the basic proof method, which partitions the system into smaller sections for individual assessment, making it easier to identify and address issues.

Using an expert system development tool improves verification and validation, particularly for end-user developers, by highlighting errors in Boolean expressions or inconsistent rules. For example, Corvid Core® offers a ‘trace’ option to follow the inference engine’s processing steps.

TMDEST is evaluated for completeness, consistency, and correctness, ensuring it meets system specifications and produces reliable results. Completeness ensures output for all possible inputs, consistency checks that results are reliable, and correctness confirms the design meets specified criteria. Validation of the knowledge base ensures high-quality information.

The VVE process starts by evaluating the system’s purpose and requirements, ensuring each module collects the necessary data and produces satisfactory results (Table III). Completeness is checked by ensuring all rules in a logic path have conclusions. Consistency is verified by checking for mutually inconsistent conclusions within the rules.

Each TMDEST module, especially the TPG methods and sample size estimation modules, is checked for consistency due to the complexity and number of rules. Correctness is confirmed by evaluating if each module meets its initial goals, even if not all methods are covered due to complexity or data requirements.

The final step is evaluating the knowledge base. It involves using published standard documents and expert knowledge to ensure the information is complete and correct. The True/False test is used to validate the knowledge, presenting randomly selected rules to experts to ensure consistency

TABLE III PURPOSE AND SYSTEM REQUIREMENTS OF EACH MODULE IN TMDEST

TMDEST Module	Purpose of the Module	System Requirements
MADT/AADT Methods Module	Evaluate different MADT and AADT estimation methods based on presence and extent of the missing data	1. AADT Estimation Methods 2. MADT estimation Methods 3. Weighting criteria 4. Presence and extend of missing data
TPG Methods Module	Evaluate four TPG analysis methods based on seasonal variation, volume trends and geographic coverage	1. TPG Methods 2. Volume Trends
TPG Groups Module	Establish the TPGs with an approximate cluster analysis and functional classification method by asking the seasonal variation and urban/rural typology questions to the user for each roadway functional class.	1. Volume Trends 2. Roadway Functional Classification 3. Seasonal Variation
Adjustment Factor Module	Improve the decision on which adjustment factors are necessary to be used to expand the collected short-duration counts for the estimation of AADTs.	1. Day/month/year of short-duration data 2. Axle or Vehicle based volume data
Sample Size Estimation Module	Evaluate the number of continuous count stations (CCS) in each TPG for statistical significance and suggest the required additional number of stations if necessary.	1. TPG numbers 2. Sample size in each TPG 3. t-statistics 4. Sample size estimation formula

IV. CONCLUSION

The expert system-based decision support tool, TMDEST, enhances the decision-making capabilities of transportation professionals involved in traffic monitoring. To our knowledge, no similar tool exists in the literature, particularly for forming traffic pattern groups (TPGs). TMDEST is designed to complement, not replace, current methods and tools for AADT estimations and TPG formations, potentially inspiring changes based on its recommendations. TMDEST's main contribution is integrating various levels of information federal guidelines, research methods, mathematical procedures, and state-level facts - into a synthesized knowledge base. It focuses on TPG analysis to improve the accuracy and reliability of data collection and processing, addressing transportation agencies' needs. While agencies often adhere to existing methods due to staff training, costs, and familiarity, TMDEST introduces users to new approaches for better MADT/AADT estimations and TPG formations. A significant advantage of TMDEST is its web-based operation, requiring no additional software. Users simply answer questions and input data to reach conclusions. The modular design allows users to perform specific tasks and enables easy updates by experts. This flexibility facilitates close collaboration with users to refine the tool. The tool's accuracy and reliability depend on the quality of user-provided data. While users are typically knowledgeable about traffic monitoring, TMDEST includes detailed explanations of estimation approaches and method selection criteria. A limitation of TMDEST is its inability to handle large datasets directly. It relies on user-provided data or approximate values for MADT/AADT estimations and coefficient of variation calculations. However, TMDEST can be adapted to integrate an agency's database for direct data extraction if desired. Future improvements include integrating an online feedback system to address limitations and gather region-specific factors influencing TPG formation. This feedback will help make TMDEST more comprehensive and user-friendly.

ACKNOWLEDGMENT

The authors would like to 8/16/2024 11:37:00 AMthank Delaware Department of Transportation (DelDOT) for providing traffic data to our research. Additionally, the authors would like to thank transportation professional in DelDOT who provided continuous feedback during the development of TMDEST.

REFERENCES

[1] C. Antoniou, R. Balakrishna, and H. N. Koutsopoulos, "A Synthesis of emerging data collection technologies and their impact on traffic management applications," *Eur. Transp. Res. Rev.*, vol. 3, no. 3, pp. 139-148, Nov. 2011, doi: 10.1007/s12544-011-0058-1.

[2] S. Bassan, "A statistical practical methodology of statewide traffic pattern grouping and precision analysis," *Can. J. Civ. Eng.*, vol. 36, no. 3, pp. 427-438, Mar. 2009, doi: 10.1139/L08-137.

[3] A. Faghri and J. Hua, "Roadway Seasonal Classification Using Neural Networks," *J. Comput. Civ. Eng.*, vol. 9, no. 3, pp. 209-215, Jul. 1995, doi: 10.1061/(ASCE)0887-3801(1995)9:3(209).

[4] A. Falamarzi, M. N. Borhan, and R. A. O. K. Rahmat, "Developing a Web-Based Advisory Expert System for Implementing Traffic Calming Strategies," *The Scientific World Journal*, vol. 2014, pp. 1-16, 2014, doi: 10.1155/2014/757981.

[5] "Office of Highway Policy Information - Policy | Federal Highway Administration," Accessed: Dec. 21, 2015. [Online]. Available: https://www.fhwa.dot.gov/policyinformation/tmguide/

[6] G. Leduc, "Road Traffic Data: Collection Methods and Applications," European Commission, Joint Research Centre, Institute for Prospective Technological Studies, Spain, Scientific Technical Note JRC 47967, 2008.

[7] M. Gastaldi, R. Rossi, G. Gecchele, and L. D. Lucia, "Annual Average Daily Traffic Estimation from Seasonal Traffic Counts," *Procedia - Social and Behavioral Sciences*, vol. 87, pp. 279-291, Oct. 2013, doi: 10.1016/j.sbspro.2013.10.610.

[8] A. Boukerche and J. Wang, "A performance modeling and analysis of a novel vehicular traffic flow prediction system using a hybrid machine learning-based model," *Ad Hoc Networks*, vol. 106, pp. 102224, Sep. 2020, doi: 10.1016/j.adhoc.2020.102224.

[9] J. Flaherty, "Cluster analysis of Arizona automatic traffic recorder data," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1410, pp. 93-99, 1993.

[10] G. Gecchele, R. Rossi, M. Gastaldi, and A. Caprini, "Data Mining Methods for Traffic Monitoring Data Analysis: A case study," *Procedia - Social and Behavioral Sciences*, vol. 20, pp. 455-464, 2011, doi: 10.1016/j.sbspro.2011.08.052.

[11] S. C. Sharma and A. Werner, "Improved Method of Grouping Provincewide Permanent Traffic Counters," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 815, pp. 12-18, 1981.

[12] A. Faghri and A. Ozden, "A Comprehensive Review and Updating of the Traffic Monitoring Program at DelDOT," University of Delaware, Delaware, Research Report, 2016.

[13] P. Jackson, *Introduction to Expert Systems*, 3rd ed., in International computer science series. Harlow, England: Addison-Wesley, 1999.

[14] J.-M. David, J.-P. Krivine, and R. Simmons, Eds., *Second Generation Expert Systems*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1993, doi: 10.1007/978-3-642-77927-5.

[15] T.-Y. Liao, T.-Y. Hu, and Y.-N. Ko, "A resilience optimization model for transportation networks under disasters," *Nat Hazards*, vol. 93, no. 1, pp. 469-489, Aug. 2018, doi: 10.1007/s11069-018-3310-3.

[16] W. P. Wagner, "Trends in expert system development: A longitudinal content analysis of over thirty years of expert system case studies," *Expert Systems with Applications*, vol. 76, pp. 85-96, Jun. 2017, doi: 10.1016/j.eswa.2017.01.028.

[17] M. Akram, I. Abdul Rahman, and I. Memon, "A Review on Expert System and its Applications in Civil Engineering," *International Journal of Civil Engineering and Built Environment*, vol. 1, no. 1, pp. 24-29, 2014.

[18] R. Mansyur, R. A. O. K. Rahmat, A. Ismail, and M. R. Kabit, "Knowledge Based Expert Advisory System for Transport Demand Management," *International Journal on Advanced Science, Engineering and Information Technology*, vol. 1, no. 6, p. 652, 2011, doi: 10.18517/ijaseit.1.6.130.

[19] E. V. Ocalir-Akunal, "Decision Support Systems in Transport Planning," *Procedia Engineering*, vol. 161, pp. 1119-1126, 2016, doi: 10.1016/j.proeng.2016.08.518.

[20] R. Frey, A. Faghri, and M. Li, "Development of an Expert System for Effective Countermeasure Identification at Rural Unsignalized Intersections," in *TRB 93rd Annual Meeting Compendium of Papers*, Washington D.C.: Transportation Research Board, 2014. [Online]. Available: https://trid.trb.org/view/1288859

[21] A. Faghri and M. J. Demetsky, "Expert System for Traffic Control in Work Zones," *J. Transp. Eng.*, vol. 116, no. 6, pp. 759-769, Nov. 1990, doi: 10.1061/(ASCE)0733-947X(1990)116:6(759).

[22] M. L. Vaughan, A. Faghri, and M. Li, "Knowledge-based decision-making model for the management of transit system alternative fuel infrastructures," *International Journal of Sustainable Development & World Ecology*, vol. 25, no. 2, pp. 184-194, Feb. 2018, doi: 10.1080/13504509.2017.1333541.

[23] F. Ülengin, Ş. Önsel, Y. İlker Topçu, E. Aktaş, and Ö. Kabak, "An integrated transportation decision support system for transportation policy decisions: The case of Turkey," *Transportation Research Part A: Policy and Practice*, vol. 41, no. 1, pp. 80-97, Jan. 2007, doi: 10.1016/j.tra.2006.05.010.

[24] A. Ozden, A. Faghri, and M. Li, "Using Knowledge-automation Expert Systems to Enhance the Use and Understanding of Traffic Monitoring Data in State DOTs," *Procedia Engineering*, vol. 145, pp. 980-986, 2016, doi: 10.1016/j.proeng.2016.04.127.

[25] S. G. Miskell, N. Happell, and C. Carlisle, "Operational evaluation of an expert system: the FIESTA approach, heuristics," *The Journal of Knowledge Engineering*, vol. 2, no. 2, 1989.

[26] J. A. Wentworth, R. Knaus, and H. Aougab, "Verification, Validation and Evaluation of Expert Systems," FHWA, Washington D.C., A FHWA Handbook (Vol. I), 1995. [Online]. Available: https://www.fhwa.dot.gov/publications/research/safety/aard/index.cfm

[27] Y. Duan, J. S. Edwards, and M. X. Xu, "Web-based expert systems: benefits and challenges," *Information & Management*, vol. 42, no. 6, pp. 799-811, Sep. 2005, doi: 10.1016/j.im.2004.08.005.

[28] B. Ruiz-Mezcua, A. Garcia-Crespo, J. L. Lopez-Cuadrado, and I. Gonzalez-Carrasco, "An expert system development tool for non AI experts," *Expert Systems with Applications*, vol. 38, no. 1, pp. 597-609, Jan. 2011, doi: 10.1016/j.eswa.2010.07.009.

[29] S. Jessberger, R. Krile, J. Schroeder, F. Todt, and J. Feng, "Improved Annual Average Daily Traffic Estimation Processes," *Transportation Research Record*, vol. 2593, no. 1, pp. 103-109, Jan. 2016, doi: 10.3141/2593-13.

[30] W. H. Schneider IV and I. Tsapakis, "Review of Traffic Monitoring Factor Groupings and the Determination of Seasonal Adjustment Factors for Cars and Trucks," Ohio Department of Transportation Office of Research and Development, Research Report, FHWA/OH-2009/10A, 2009. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/17542

[31] T. Wright, P. S. Hu, J. Young, and A. Lu, "Variability in Traffic Monitoring Data," Tenesse, Research Report DE-AC05-96OR22464. [Online]. Available: https://www.fhwa.dot.gov/ohim/flawash.pdf

[32] "Use of Data From Continuous Monitoring Sites," Cambridge Systematics, Washington D.C., 1994. [Online]. Available: https://rosap.ntl.bts.gov/view/dot/30663/dot_30663_DS1.pdf