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APPLIED RESEARCH

Dynamic Optimal Vehicle Selection for Cooperative Positioning Using Low-Cost GNSS Receivers

THANASSIS MPIMIS [1], THEODORE T. KAPSIS [2], VASSILIS GIKAS [1], AND ATHANASIOS D. PANAGOPOULOS [2], (Senior Member, IEEE)

[1] School of Rural, Surveying and Geoinformatics Engineering, National Technical University of Athens, 15780 Athens, Greece
[2] School of Electrical and Computer Engineering, National Technical University of Athens, 15780 Athens, Greece

Corresponding author: Athanasios D. Panagopoulos (thpanag@ece.ntua.gr)

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ABSTRACT The recent developments in the Global Navigation Satellite Systems (GNSS) and the advent of Intelligent Transportation Systems (ITS) have accelerated the need for accurate, reliable, and robust land vehicle positioning. Current low-cost, single-frequency GNSS receivers are universally available and have already been employed in a variety of urban mobility applications. However, low-cost GNSS receivers provide low (5-15 m) accuracy that deteriorates rapidly in deep urban and harsh environments imposing a significant impact on the effectiveness and the reliability of critical ITS services. In this paper, a novel vehicle ranking and selection methodology for cooperative positioning (CP) is developed aiming at capitalizing on low-cost GNSS receivers' potential and maximizing their benefits in safety-critical vehicular applications. The proposed method is based on the Multi-attribute Decision-Making (MADM) theory and provides a prioritization of the neighboring vehicles in the vicinity of a target vehicle using criteria related to position accuracy and reliability. By selecting the optimal neighbor vehicle for CP, the low-cost receiver of the target vehicle enhances its location-awareness, and hence, its absolute/relative positioning accuracy. The proposed optimal vehicle selection process was inspired by the Cooperative-Differential GNSS (C-DGNSS) technique. An additional contribution of the proposed methodology is the expansion of the "moving base station" concept for use in ITS. Various MADM algorithms are considered and simulated employing real experimental data from multiple, low-cost GNSS receivers. The optimal MADM algorithm proposed is TOPSIS because the derived rankings offer maximum stability and similarity with Average Correlation Index (ACI) = 0.78, thus satisfying the requirements for critical applications.

INDEX TERMS Accuracy improvement, cooperative positioning, global navigation satellite system (GNSS), intelligent transportation systems (ITS), low-cost GNSS, multi-attribute decision-making (MADM), NMEA, ranking methods, RTCM, TOPSIS, VANETS, vehicular networks.

I. INTRODUCTION

Low-cost GNSS receivers are increasingly used in a variety of mobility applications today stemming from the higher number of available navigation satellites and signals (>100) [1]. Such units are usually patch-antenna-equipped receivers with multi-constellation tracking capabilities that enable either a single or dual-frequency functionality. Moreover, they are lightweight, require a small power supply, and work in a variety of temperature conditions while featuring networking capabilities [1]. The low-cost and ultra-low-cost GNSS receivers are currently mass-produced for commercial location-based services (LBS) and for equipping tracking devices of various types – for instance, smartphones,

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wearables, and drones [2]. In [1] they are paired with Real-Time Kinematic (RTK) positioning or inertial sensory units and have been proven accurate enough for certain non-safety-critical applications under good channel conditions.

However, the excessive error budget accumulated in low-cost receivers and their low availability in the city environment has restricted their use, especially for vehicular, safety-critical applications. This is mainly due to signal occlusion, multipath, and radio interference [1], [2]. As a result, low-cost GNSS receivers alone cannot reach the full potential of satellite positioning and, therefore, they are used complementary to other sensor types to increase redundancy and reliability in position fixing [3], [4], [5].

Various positioning schemes with low-cost receivers have been proposed to study the value of GNSS in connected and autonomous vehicular applications. In [6] and [7] the authors consider handheld smartphones equipped with GNSS receivers and Inertial Measurement Units (IMUs) for low-cost ITS usage. They thoroughly investigate smartphone precision and trueness by comparing their accuracy performance against a high-end GNSS/IMU system. The cruising and maneuvering assessment tests were conducted in both open and shadowed areas. The results showed variability in the error budget between the different smartphone manufacturers but also a high potential for safety-critical applications.

The use of IMUs is a good technique to support GNSS and provide a solution in areas where satellite signal outages occur for short time gaps [8], [9], [10]. Inertial sensors improve and smooth the PVT solution derived from the GNSS receiver. But in the case of a prolonged degraded GNSS solution, the errors of the IMU sensors are so large that they ultimately do not help and do not improve the final solution [10]. Thus, the only technique that may improve the GNSS solution is the cooperative positioning technique.

In this work, a dynamic algorithm for assisting the positioning of a target vehicle based on a number of available candidate neighbors is proposed based on Cooperative-Differential GNSS (C-DGNSS). The key idea resides on the basic principle of GNSS differential positioning, not through pseudorange corrections, but phase corrections [11], [12], [13], [14]. All vehicles in the neighborhood share their current PVT information, their positioning quality metrics, and GNSS systematic corrections (atmospheric delays, clock errors, orbital data errors) for all satellites (SVs) in view.

The target vehicle reviews in a sequential manner the incoming PVT information and decides in an optimal and dynamic manner which neighbors to use for retrieving GNSS corrections for improving/updating its own PVT state.

The computation of baseline vectors/IVRs is not required in this proposed C-DGNSS algorithm. The transmitted PVT data are in the form of National Marine Electronics Association (NMEA) sentences and are elaborated in subsequent sections [16], [17]. The differential corrections are in the form of Radio Technical Commission for Maritime (RTCM) Services streams [18], [19]. Figure 1 depicts the C-DGNSS procedure.

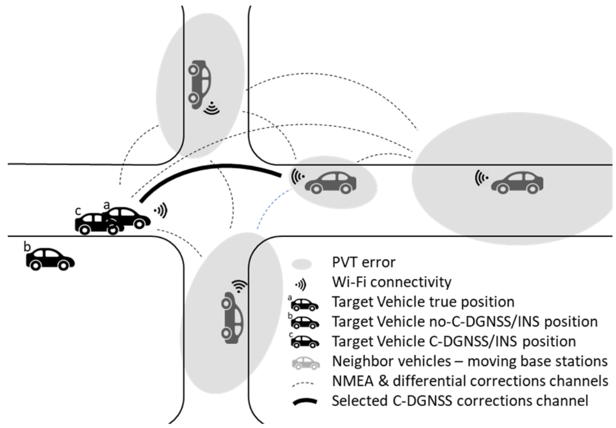


FIGURE 1. Schematic view of the Cooperative-Differential GNSS (C-DGNSS) positioning layout.

For this purpose, several multi-objective criteria and multi-attribute decision-making (MADM) methods are introduced to fully process all incoming information from the vehicles in the neighborhood, including their position accuracy, dilution of precision (DOP), integer ambiguity status, etc. The major contributions of this article are:

- A comparative analysis of various MADM methodologies is presented and a dynamic MADM selection algorithm based on Spearman's rank correlation is proposed. The proposed algorithm ranks and selects the optimal MADM method that exhibits the highest-ranking consistency and stability from a set of several other MADM methods.
- The chosen optimal MADM method is then used to rank and select the optimal neighbor of the available vehicles surrounding the target vehicle using a multitude of objective criteria that characterize their position information.
- Actual experimental data from low-cost GNSS receivers are employed to perform the MADM simulations that cover various operating scenarios (i.e., deep urban, suburban, and rural areas).
- The employed data are extracted from NMEA sentences which are universally produced irrespectively of GNSS receiver manufacturers. The values of the decision criteria adopted are obtained from the NMEA data.
- Time series of criteria values related to position information, MADM methods ranking representations as well as alternative vehicle rankings results with rank scores are exhibited. Especially, the neighbor vehicles' rankings are derived solely from the NMEA PVT data.

II. COOPERATIVE POSITIONING RELATED WORK

The precision, accuracy, and reliability of the low-cost GNSS receivers can be significantly improved through cooperative or collaborative positioning (CP) [11]. Vehicle-to-vehicle (V2V) communication aiming to connect vehicles is a critical application of the 5G technology that will enable the provision of safety-critical services in deep urban areas and will allow the exchange of real-time Position, Velocity, and Time (PVT) information leading to computing inter-vehicular ranges (IVRs), carrier phases, relative speed, and more [12]. At the single-user level, using DGNSS techniques along with local GNSS raw data, and differential corrections are estimated the baseline vectors (Euclidean distances) between moving GNSS receivers [2]. The integration of this IVR will improve both the accuracy and precision of the target vehicle [10].

In [2] the authors provide a Proof of Concept regarding the feasibility of a GNSS-based CP between 4G/LTE smartphones equipped with ultra-low-cost GNSS receivers. A near-real-time sharing of raw GNSS observations among the smartphones is achieved which enables computation of IVRs and consequently offers a hybrid PVT solution. The experimental results exhibit an average accuracy improvement of over 40% compared to standalone GNSS. In [12] the authors propose and evaluate four distinct CP methods to estimate inter-vehicular ranges with double differencing of the raw code observables being the most accurate one. A dual-vehicle scenario with field testing in various environments is considered. In [14] the authors adopt the "moving base station" CP technique by placing two low-cost GNSS receivers on board the same moving vehicle at a pre-set distance and then provide preliminary results from the testing of this technique compared to an RTK GNSS solution using a virtual reference station. The experiment was carried out along a 9 km-long urban trajectory. The trueness (i.e., how far the measurement is from the true value) of the baseline length has shown an improvement of the order of 40% when using the moving base station technique instead of RTK GNSS. In [15], [16], and [17] additional information on the proposed C-DGNSS approach is provided while also preliminary results appear. In [18] and [19] more recent related work to cooperative vehicle positioning, navigation, and localization is reported.

TABLE 1. Typical values of communication parameters for safety-critical ITS applications.

Scenario	Beacon Rate (Hz)	Latency (ms)	Reliability (%)
Safety-critical vehicular CP	10-20	1-50	$\geq$ 99.999

Safety-critical applications pose very strict requirements regarding the beacon rate, latency, and reliability while the data rate can be a few tens of Mbps. Table 1 summarizes the radio-network communication requirements for safety-critical vehicular CP based on [20]. The latency parameter includes both the transmission-related delay and the processing-related delay. The reliability parameter (i.e., the percentage of time in which packets are delivered in the correct order and without losses), is also crucial because of the high environmental dynamicity which could lead to outdated or degraded position estimation.

III. MULTI-ATTRIBUTE DECISION-MAKING METHODS

In order to apply the proposed CP scheme and benefit from the exchange of GNSS code corrections, the target vehicle (low-cost GNSS receiver) needs to rank the moving vehicles in the vicinity and select the optimal neighbor. A MADM algorithm is proposed as a basis for neighbor selection using a variety of criteria, weights, and alternatives [25], [26]. MADM methods are designed to determine the most satisfying of a number of antagonistic alternatives or to provide ranking capabilities. The prioritization of the alternatives is achieved by evaluating and comparing their performances across certain weighted criteria [23], [24], [25], [26]. The MADM algorithms converge to the optimal solution, and are useful, as long as there is no evident best alternative. This may happen when an alternative performs notably better than all the others and, in all criteria, so in this case, the optimal alternative is prominent.

In practice, the criteria values are stored in a decision matrix (M $\times$ N), where M is the number of alternatives and N is the number of criteria. The importance of each criterion on the outcome is expressed by assigning a weight to it. The adoption of the criteria weights vector could be a challenging task and one can either employ particular weighting techniques or set them empirically [25], [26]. Most MADM methods are based on the principles of linearity and causality. That is the decision-making process is regarded as one-way, as the final decision must be determined by the criteria and follow the synthesis process. This traditional approach is also called the linear aggregation approach [25].

Currently, there exists a variety of MADM methods that can be grouped and categorized in terms of their ranking characteristics. Table 2 provides a taxonomy of some well-known MADM methods [25], [26].

The scoring-based class algorithms include techniques such as the SAW, COPRAS, MOORA, and GRA. They are considered the least complex, fast, cheap, and easy-to-implement techniques. Scoring methods are also plain and easy to interpret by the decision-maker, they combine all the criteria values and weights into a single output and are suited for evaluating a specific alternative. Their drawbacks stem from the unrealistic assumption that the attributes can be linearly aggregated. The need for normalization and positive attribute values as well as the ranking inconsistency when the input values are largely fluctuating are also drawbacks of this class of MADM algorithms [25], [26].

The distance-based class includes methods such as the TOPSIS, VIKOR, CODAS, MABAC, D'IDEAL, and ORESTE. This group of algorithms computes the distances from the ideally best and worst points and ranks the alternatives via a compromise between the two distances. These MADM algorithms feature a medium complexity, and they are sufficiently stable even if the input data fluctuates, assum-

TABLE 2. Taxonomy of main MADM methods.

MADM class	MADM method
Scoring-based	Simple Additive Weighting (SAW). Complex Proportional Assessment (COPRAS). Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA). Grey Relational Analysis (GRA).
Distance-based	Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Visekriterijumsko Kompromisno Rangiranje (VIKOR). Combinative Distance-based Assessment (CODAS). Multi-Attributive Border Approximation Area Comparison (MABAC). Displaced Ideal Method (D'IDEAL). Organization, Rangement Et. Synthese De Donnes Relationnelles (ORESTE).
Pairwise Comparisons	Analytic Hierarchy Process (AHP). Analytic Network Process (ANP).
Outranking	Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE). Elimination and Choice Expressing Reality (ELECTRE).
Utility/Valuate	Multi Attribution Utility Theory (MAUT). Multi Attribution Value Theory (MAVT).

ing unchanged best and worst ideal points; however, they require normalization of the decision matrix. Also, the use of Euclidean distance mishandles strong correlations between the attributes [25], [26].

The pairwise comparisons MADM class includes AHP and ANP techniques and is considered the most demanding in terms of computational time, complexity, and mathematical calculations. These techniques employ a hierarchy structure that can handle both qualitative and quantitative data types without normalization needs but are restricted to independent attributes. This makes them unsuitable for real-world applications. Particularly, the AHP technique is judgmental and depends on the subjective preferences of the stakeholders leading to instabilities. In contrast, ANP circumvents the need for independence and is better suited for criteria with interrelationships [25], [26].

PROMETHEE and ELECTRE techniques and their extensions are associated with the outranking class. They employ a binary concordance model between the alternatives leading to partial or complete ranking based on wins and losses. Usually, a preference function is adopted that makes use of predefined threshold values. They can handle both qualitative and quantitative data types with no need for normalization; however, due to the binary outranking relations between alternatives they exhibit higher time complexity almost quadratic, especially as the number of alternatives and attributes increases [25], [26].

Finally, the utility/valuate class includes MAUT and MAVT techniques which also take into account the personal preferences of the decision-maker and can handle uncertainties in the data. Contrarily, they require a huge volume of input data and the results are subjective [25], [26].

The stability and/or ranking consistency of the performance of the different MADM techniques regarding the number of alternatives, appropriate balancing of the weights, and the measurement scales form part of a sensitivity analysis. Those techniques that retain statistically the priorities and ranking of alternatives when altering the input data are deemed to be the more robust ones, and consequently, they suit real-time applications. Another problem is the rank reversal phenomenon that occurs in all classes and methods. It occurs when a duplicate alternative or a worse-scoring alternative is added, removed, or replaced then the top ranks might reverse which is inconsistent [25], [26].

In [27] the challenge of network selection in multi-access radio network environments is formulated as a decision-making problem. The authors propose ranking techniques based on utility functions, and MADM methods. Notably, the method's stability is considered a crucial parameter in radio networks in order to avoid unnecessary selections (handovers). For real-time cooperative positioning applications with low latency, high reliability, and a fast-changing operating environment the pairwise comparison methods (AHP, ANP) and utility methods (MAUT, MAVT) are excluded due to their high complexity, the huge amount of data required, and their subjective nature.

IV. GNSS CRITERIA SELECTION DESCRIPTION

MADM analysis presupposes several criteria or attributes that altogether characterize the quality in the GNSS position of the engaged vehicles. Considering real-time applications, these criteria must be highly uncorrelated and preferably of a limited number (up to 5 or 6) in order to evaluate adequately the accuracy of the vehicle position without adding latency and overhead to the decision-making methodology. The NMEA constitutes a data specification between GNSS receivers (and other types of instruments) readily available regardless of GNSS receiver manufacturer or grade [21], [22]. The universally produced NMEA 0183 sentences have a serial format filled with specific data fields that contain detailed positioning information. For instance, message $GNGNS yields geographic information such as the geographic longitude and latitude, altitude, the number of GNSS satellites in receipt, and the horizontal/vertical dilution of precision (DOP) metric. Similarly, the $GNGST message provides position statistics such as the Root-Mean-Square (RMS) values of the horizontal/vertical standard deviations in position, [21], [22]. These messages are fed as input to the MADM algorithm.

In this work, the following five attributes are taken into account for the vehicular system under investigation: (i) the number of satellites in view (NS), (ii) the root mean square of the range observations in the L1 frequency band (Range RMS), (iii) the standard deviation of the horizontal coordinates point fix (Hz std), (iv) the ambiguity status of the position solution (Amb Stat), and (v) the horizontal dilution of precision (HDOP). The NS equals the number of GNSS satellites in receipt from the GPS, GLONASS, Galileo, and BeiDou systems, the Range RMS is measured in meters and expresses the radius of the error circle within which about 68% of L1 position fixes lie, the Hz std is measured in meters and expresses the horizontal accuracy error in position, and the Amb Stat denotes the GNSS receiver's integer ambiguity status. Thus, Amb Stat may yield an autonomous solution with a position accuracy of ~ 10 m, differential GPS (DGPS) with an accuracy of ~ 3 m, a float solution with an accuracy of ~ 0.30 m, and a fixed solution with an accuracy of ~ 0.02 m. The fixed solution of a neighbor car may have been derived from RTK or Precise Point Positioning (PPP). Finally, the HDOP reveals the effect of the DOP on the horizontal position value. The more visible satellites low in the sky, the better the HDOP and the horizontal position (latitude and longitude) are.

From the selected NMEA messages discussed above, only specific fields are used in the MADM algorithms (input). Table 3 shows the list of criteria used per NMEA sentence. Every single vehicle broadcasts these criteria, which reflect the quality of its PVT solution. The MADM algorithm running on the target vehicle uses the received criteria to rank the in-range neighbor vehicles.

TABLE 3. Criteria used for implementing MADM technique in C-DGNSS positioning.

a/a	Criterion name	NMEA sentence	NMEA field no
1	number of satellites	GNS	10
2	range RMS	GST	2
3	horizontal std	GST	6, 7
4	integer ambiguity status	GNS	6
5	HDOP	GNS	8

V. SIMULATIONS SCENARIO/CRITERIA VALUES

The first step in testing and validating the alternative MADM methods applied in dynamic C-DGNSS calls for using experimental data of criteria values. C-DGNSS application belongs to the CP family, in which neighboring vehicles transact data that refer to standardized *NMEA* sentences containing PVT, position accuracy, and integrity information. These sentences constitute the criteria (input) that the MADM algorithm uses to rank the neighboring moving vehicles (output) and select the optimal alternative.

The recorded data used for implementing the testing and validation process were acquired using six-passenger vehicles that moved simultaneously at different trajectories spanning about 2000 epochs ($\sim$33.3 min), whilst each trajectory consisted of variable observation conditions. Recorded trajectories include sections with: (i) open sky conditions (cut-off elevation angle $< 10°$. The multipath effect is negligible) [28], (ii) urban environment with narrow streets and high-rise buildings (cut-off elevation angle 10° to 30°. Multipath has medium impact) [28], and (iii) semi-urban segments with tall trees of dense foliage, resulting in severe attenuation and partial blockage of the satellite signal (Cut-off elevation 20° to 60°. Strong multipath impact) [28]. Each vehicle is equipped with a low-cost or middle-range GNSS receiver connected with a patch antenna placed at the top of the vehicle. The middle-range receivers have the capability of an RTK solution, while the low-cost are not equipped with this option. A simulation framework was implemented using the MATLAB® toolbox for realizing the MADM simulations.

The GNSS receivers from all six vehicles were configured to compute the PVT solution and report it at 1 Hz (2000 s in total). The position solution is standardized in NMEA GNS and GST messages. The data are derived from the PVT solution only, ignoring how GNSS signals interact with the environment.

Of the six passenger vehicles that were used, the first vehicle (veh. #1) is the target vehicle and the remaining five ones (veh. #2, veh. #3, veh. #4, veh. #5, veh. #6) are the neighbor vehicles. Figure 2 shows a plot of the number of satellites in view of the GNSS receiver of each vehicle. From Figure 2 it is evident the variability in observation conditions for the contributing vehicles.

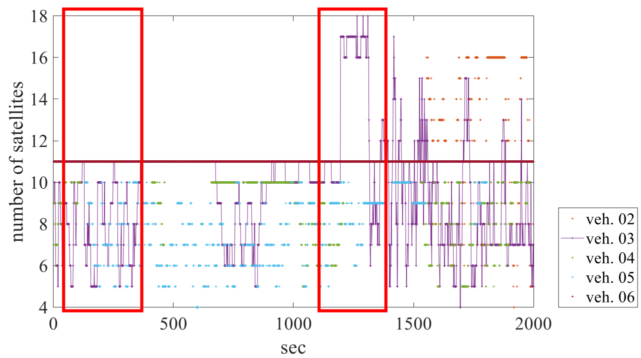


FIGURE 2. Number of satellites in view per neighbor vehicle (veh. #02/03/04/05/06) for the entire trajectory.

For instance, veh. #6 has a stable RTK fixed solution, as it is moving in a suburban environment. The number of satellites is constant during its trajectory whilst showing up only a few fluctuations. The number of satellites illustrated is the number of common satellites between the vehicle and the base receiver.

The high variability observed in the satellites' observation (NS) in Figure 2, is due to the different urbanization levels and the non-line-of-sight reception due to the urban canyons. Figure 3 illustrates the Horizontal standard deviation (Hz std) of each vehicle along its trajectory. As expected, as the number of satellites decreases the Hz std increases. Also, the greater the fluctuation of the satellites in view the worse the Hz std becomes.

Figures 2 and 3 illustrate the conditions that existed during data collection and how satellite observations and their variability affect the quality of the receiver PVT solution. For example, in Figure 2 there are two red boxes that emphasize a period with a few satellites in view and high fluctuation (left). The right box surrounds a period with several satellites in view and low fluctuation. Similarly in Figure 3, the corresponding boxes are shown, where the left shows a high horizontal position rms, while the right a period of low horizontal position rms, respectively, which are expected to.

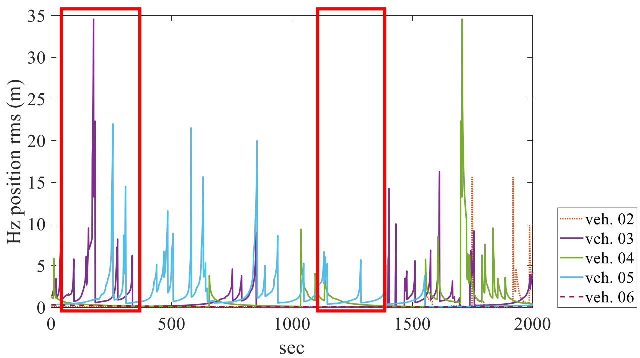


FIGURE 3. Horizontal position rms per neighbor vehicle (veh. #02/03/04/05/06) for the complete trajectory.

VI. MADM METHODS COMPARISON AND JUSTIFICATION

In the proposed C-DGNSS localization approach, the vehicles in the vicinity of the target vehicle share their PVT data with it. Subsequently, a decision algorithm selects the optimal neighbor for cooperation (Table 2). In this study, a set of six MADM methods are tested and cross-compared, two from each MADM family. These are the SAW, CODAS, COPRAS, TOPL1, PROMETHEE, and ELECTRE. TOPL1 is the TOPSIS method employing Euclidean distances of each alternative from the positive and negative ideal solutions while the Gaussian preference function was employed for PROMETHEE [25], [26]. The AHP class was omitted because it's strongly subjective and computationally complex while the utility class requires a lot of input data to converge fast to a decision.

The decision matrices are filled with dynamic criteria data obtained from simultaneous trajectories of the alternative vehicles. The results of each MADM method suggest a ranking of the contributing vehicles for a specific decision matrix corresponding to a given timestamp (epoch). In other words, for every epoch of criteria values, there are as many rankings as the number of MADM methods.

It is proposed that the best MADM method to be selected should give rankings strongly consistent with those obtained using the other methods and with good agreement. Also, it should rely on as simple as possible computations providing real-time, fast, and reliable results. The Spearman's rank correlation coefficient (rho) is widely used as a measurement of similarity between different rankings.

In this study, we make use of the correlation coefficient rho to compare the MADM algorithms and select the most appropriate one. The coefficient rho for computing the correlation between the rankings of columns C_a, C_b is given by:

$$rho\,(C_a, C_b) = 1 - \frac{6\sum d^2}{n\,(n^2-1)} \tag{1}$$

where, d is the difference between the ranks of two columns (i.e., two MADM methods) and n is the length of each column (number of ranks). For an input ranking matrix $\mathbf{X}$ of multiple columns, $rho(\mathbf{X})$ returns a matrix with the correlations between each pair of its columns.

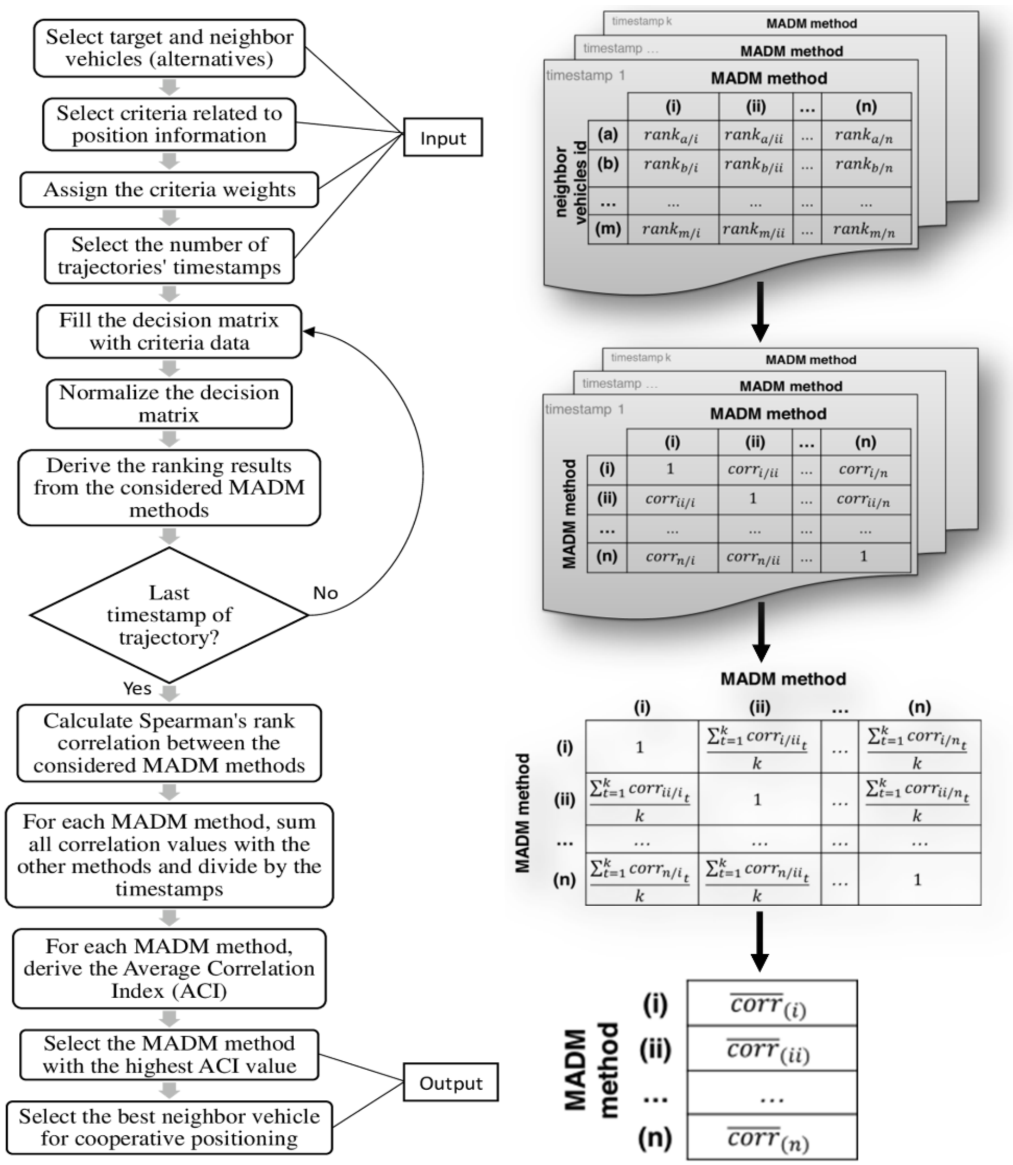
The callout diagram shown in Figure 4(a) depicts the algorithmic steps used to propose the most preferred MADM method. In this diagram (n) MADM methods and (m) alternative vehicles are examined for a trajectory of (k) timestamps, while in every timestamp (i) equal-weighted criteria are available. The assignment of identical criteria weights, although an ideal situation in practice, is done to avoid a predominant attribute while evaluating the methodologies. Every timestamp corresponds to a column that includes the ranking of alternative vehicles of each MADM method ($\mathrm{rank}_{m/n}$), and thus the dimensions of the ranking matrix for every timestamp are (m × n).

The subsequent step for computing the (m × n) ranking matrix resides in the correlation coefficient matrix calculation using Spearman's correlation method (Figure 4(b)). The result is a (n × n) symmetric positive semidefinite matrix with unitary diagonal at every timestamp. In order to calculate the total correlation coefficient matrix from the complete trajectory, a sum along the third dimension is performed, and then it's divided by the total number of timestamps. In the final step, a metric equivalent to the Rank Similarity Index in [29], the average correlation index (ACI) $corr_i$ is computed by averaging the previous correlation values. The ACI is a statistical benchmark to measure the ranking stability and consistency of the investigated MADM methods. This leads to better performance by avoiding unnecessary handovers, e.g., when input criteria data greatly fluctuate, when selecting the optimal neighbor vehicle. Conclusively, the MADM method with the largest ACI is the most preferred one, as it yields consistent rankings and is in good agreement with all the other methods for the whole trajectory [29]. In our case, a trajectory of k = 2000 timestamps subject to i = 5 criteria is examined using m = 5 alternative vehicles (veh. #02 – veh. #06) while the ranking results of n = 6 different MADM algorithms are compared.

Table 4 summarizes the results associated with Figure 4. Clearly, the largest ACI value is observed in methods SAW and TOPL1 while the outranking class of ELECTRE and PROMETHEE is the worst-performing MADM classes.

According to Table 2, the SAW method belongs to the scoring-based class, while TOPL1 belongs to the distance-based MADM class. From the qualified methods above those that belong to the Distance-Based MADM class (TOPL1 and COPRAS) are preferable due to their stability even for variable data, and due to medium complexity.

TOPSIS exhibits a time complexity of O(n) when calculating the ideal best and worst points, and O(n^2) for normalization and weighting, where n is the input size [30]. In our MATLAB® simulations, the estimated latency was a few milliseconds implying its applicability for smartphones, PDAs, or other handheld devices. Figure 5 depicts the results



(a) (b)

FIGURE 4. **The step-by-step flowchart of the proposed MADM selection algorithm (a), and the Spearman's correlation method and the calculation of the Average Correlation Index (ACI) values to extract the most consistent MADM method (b).**

TABLE 4. **Average correlation index for six MADM methods.**

Method	ACI
SAW	0.78
COPRAS	0.73
CODAS	0.76
TOPSIS L1	0.78
PROMETHEE	0.46
ELECTRE	0.68

of the TOPL1 MADM method that corresponds to the rank I selection vehicle ID along the trajectory. These results are derived using the MAX normalization method (i.e., divide criteria values by the maximum value) and an assumption of equal weights of criteria for the decision matrix. It is observed that vehicle #02 remains in rank I for the most timestamps, compared to other vehicles, while vehicle #05 is the least selected in rank I along the whole trajectory.

Further results using additional normalization methods and weight combinations may be implemented. For example, normalization of the decision matrix with the column-wise sum of the criteria values or applying linear (max-min) scaling, log-scaling, and vector normalization. Moreover, the weights should reflect the safety-critical CP requirements, and different weightings might yield different ranking results.

Figure 6 illustrates the mean ranking of alternative vehicles only for the cumulative top two ranks (I+II) in the overall trajectory for all six MADM methods. The upper plot of

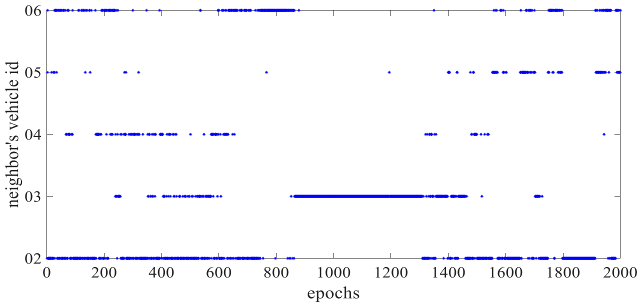


FIGURE 5. Rank I vehicle during trajectory, using MAX normalization method, TOPL1 MADM method and equal weight among criteria.

Figure 6 assumes equal weights whilst the bottom plot adopts a weight matrix w = [0.1 0.8/3 0.8/3 0.8/3 0.1]. Obviously, the rankings of vehicles #02 and #04 remain almost the same, while the rankings of vehicles #03, #05, and #06 change slightly. Also, vehicle #02 remains at the top of ranks I+II for approximately 80% of all timestamps compared to other vehicles along the trajectory. On the other hand, vehicle #04 is the least selected alternative for only about 10% of the time in I+II ranks.

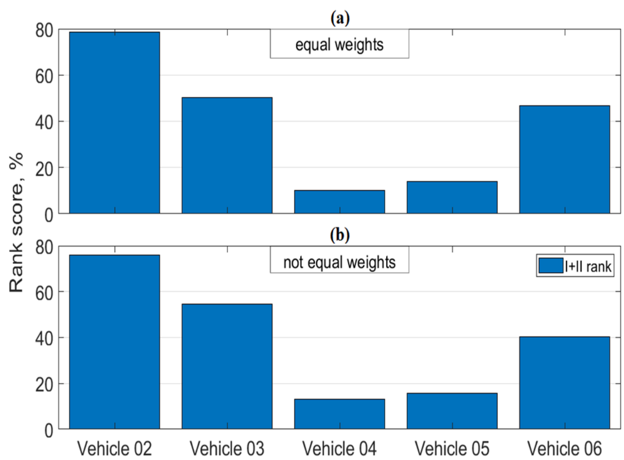


FIGURE 6. Mean ranking of I+II rank positions of alternative vehicles for the entire trajectory using MAX normalization and six MADM methods. (a) Equal weights. (b) Unequal weights.

VII. CONCLUSION

In this article, a cooperative positioning solution based on Multi-attribute Decision-Making is developed aiming at exploiting the potential of low-cost GNSS receivers and maximizing the benefits of GNSS positioning for safety-critical vehicular applications. The proposed decision methodology for optimal neighbor selection exhibits low latency suggesting applicability for near real-time usage. It can also be implemented universally with the employment of NMEA sentences. It provides a ranking of the neighboring vehicles using criteria related to quality metrics in position. In order to derive the optimal neighbor and methodology, six MADM algorithms are considered and simulated employing actual experimental data over various environmental settings that employ multiple, low-cost GNSS receivers. The numerical results are presented and discussed and the best MADM algorithm is investigated. From the preceding analysis, the distance-based TOPSIS method is proposed because the derived rankings offer maximum stability and similarity (ACI = 0.78) with the rankings of all the considered methodologies. The proposed methodology may be implemented using portable devices (e.g., smartphones and tablets) in the sphere of the smart cities concept or for recreational activities (e.g., team hiking). For example, employing more affordable localization tools for connected vehicles can lead to enhanced ITS services with overall economic benefits.

Finally, the MADM simulations in this work with the employed dataset derived from a variable conditions' trajectory successfully demonstrated the feasibility of our proposed methodology and indicated TOPSIS and SAW to be superior. Under conditions, a real-time application of the C-DGNSS algorithm can be realized using real-time PVT data in a CP setup where the participating vehicles have the MADM algorithm implemented and installed.

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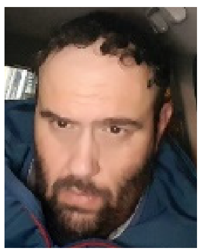
THANASSIS MPIMIS received the Diploma degree in surveying engineering from the Survey and Rural Engineering School, National Technical University of Athens (NTUA), the B.Sc. degree in industrial management and technology from the University of Piraeus, and the M.Sc. degree in techno-economic. He is currently pursuing the Ph.D. degree in geodesy—navigation. He is the author of papers in international peer-reviewed journals and conference proceedings. His research interests include interconnection between geodetic equipment and heterogeneous sensors and in navigation using satellite receivers and inertial measurement units.

THEODORE T. KAPSIS was born in Megalopolis, Greece, in September 1994. He received the Diploma degree in electrical and computer engineering (ECE) from the National Technical University of Athens (NTUA), Athens, Greece, in 2018, where he is currently pursuing the Ph.D. degree. His scientific research topic is "Next-generation radio communication systems" and the Ph.D. thesis is related to data analysis, optical satellite communication networks, 5G wireless communications, and channel modeling for satellite and terrestrial systems. He has published more than ten papers in international conferences and journals.

VASSILIS GIKAS received the Diploma degree in surveying engineering from the National Technical University of Athens (NTUA), Greece, and the Ph.D. degree in geodesy from the University of Newcastle upon Tyne, U.K. He is currently a Professor with NTUA. In the past, he worked for the oil exploration industry in the U.K. and USA as a Positioning and Navigation Scientist and a Supervisor with the Seismic Acquisition Programs in Europe and West Africa. His principal research interests include geodesy and GNSS, methods and multi-sensor systems for positioning and navigation, and dynamic monitoring and analysis of structures and physical processes. He is a member of several professional and scientific organizations. He is currently the Co-Chair of Commission 4 "Positioning and Applications," International Association of Geodesy, and the Vice-Chair of WG 6.1 "Deformation Measurement and Analysis" of the International Federation of Surveyors.



ATHANASIOS D. PANAGOPOULOS (Senior Member, IEEE) was born in Athens, Greece, in January 1975. He received the Diploma degree (summa cum laude) in electrical and computer engineering and the Dr. Engineering degree from the National Technical University of Athens (NTUA), in July 1997 and April 2002, respectively. He has been a Full Professor with the School of Electrical and Computer Engineering, NTUA, since September 2021. He has published more than 190 articles in international journals and IEEE TRANSACTIONS and more than 240 papers in conference proceedings. He has also published more than 35 book chapters in international books. His research interests include radio communication systems design, wireless and satellite communications networks, and mobile computing systems. He was a recipient of URSI General Assembly Young Scientist Award, in 2002 and 2005. He was also a co-recipient of the best paper awards in IEEE RAWCON 2006 and IEEE ISWCS 2015. He has participated to ITU-R and to ETSI Study Groups and he is also a member of Technical Chamber of Greece. He was the Chairperson of the IEEE Greek Communication Chapter for eight years. He has led as a Principal Investigator many research and development programs funded by EU and European Space Agency. He is also a member of the Hellenic Telecommunications and Post Commission (EETT). Finally, he has served on the editorial boards for *Physical Communication* (Elsevier), IEEE TRANSACTIONS ON ANTENNAS AND PROPAGATION, and IEEE COMMUNICATION LETTERS.