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A hybrid MCDM approach for optimizing fuel consumption and mitigating air pollution in shipping: A case study using DEMATEL and ANP

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Abstract
Fuel consumption represents a pivotal factor in determining operational costs within maritime transportation, with direct implications for energy efficiency, environmental sustainability, and air pollution. This study aims to identify and evaluate the key determinants influencing fuel consumption, with the objective of optimizing these factors to enhance overall energy efficiency. A Multi-Criteria Decision-Making (MCDM) methodology was employed to systematically rank and prioritize the most significant criteria impacting fuel efficiency. The findings of the study indicate that compliance with sea conditions, optimal ship speed and the expertise of shipmasters (C3.2) are the most influential factors, followed by voyage planning that accounts for sea and weather conditions (C3.7). These results emphasize the critical role of operational strategies and the decision-making capabilities of personnel in minimizing fuel consumption. Moreover, the study identifies the significant contribution of maintenance practices, adherence to regulatory frameworks and environmental factors in shaping fuel efficiency outcomes. Quantitative analyses confirm that the implementation of energy-efficient practices can result in substantial cost savings and reductions in emissions. However, the achievement of stringent emission reduction targets may impose financial burdens on shipping companies, necessitating significant investments in fuel-efficient technologies and operational optimizations. Future research should focus on longitudinal voyage analyses, incorporating larger sample sizes and the development of mathematical models that align with the CO2 reduction targets set by the International Maritime Organization (IMO) for the years 2015, 2020, 2025, and 2030. This research provides valuable insights for maritime industry stakeholders and contributes to ongoing policy discussions, advocating for the establishment of standardized fuel consumption management practices that promote a more sustainable and economically efficient future for the shipping industry.

Keywords
Fuel consumption in ships, CO2 emissions, air pollution, multi-criteria decision-making (MCDM)

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Introduction

Maritime transportation plays a crucial role in global economies, with fuel expenses being the largest operational cost for shipping companies. As fuel prices have steadily increased since the 2000s, fuel has become a resource that must be managed efficiently to maintain profitability in changing financial conditions.[1] To address this challenge, the primary focus of cost-saving strategies has been on reducing fuel consumption, which directly impacts shipping expenses and environmental sustainability. Excessive fuel consumption not only increases operational costs but also contributes to greenhouse gas emissions and harmful air pollutants, including particulate matter and nitrogen oxides, which exacerbate global air pollution and public health risks.

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The maritime industry faces a dual challenge: balancing the economic pressures of reducing fuel costs while addressing the environmental impact of emissions. Ships are among the largest contributors to global sulfur oxides (SOx) and nitrogen oxides (NOx) emissions, which significantly degrade air quality in port cities and coastal regions. Furthermore, the CO2 emissions from maritime transportation account for nearly 3% of global greenhouse gas emissions, a figure projected to rise unless proactive measures are taken. The intersection of fuel efficiency and environmental responsibility underscores the urgency for adopting strategies that not only reduce fuel consumption but also mitigate the broader impact on air quality and climate change.

Fuel consumption can account for 12% to 25% of a ship's total voyage cost and this expense is strongly influenced by factors such as the ship's speed, load and operational conditions.[2] For instance, fuel consumption varies significantly depending on whether a ship is sailing with ballast or carrying cargo and the daily fuel consumption decreases as the fuel weight reduces, affecting the ship's overall weight.[2] To optimize fuel use, reducing wait times at ports and during maneuvers by adjusting sailing speed can lead to greater fuel efficiency, particularly for cargoes with flexible delivery schedules.[3]

The use of new-generation ship designs and technologies to reduce both voyage operation costs and greenhouse gas emissions is a significant focus for the maritime industry. According to the International Maritime Organization (IMO), it is possible to reduce ships' carbon dioxide emissions by up to 50% through the use of innovative design technologies.[4] From a technical point of view, reducing a ship's speed by 10% can decrease engine fuel consumption by approximately 27%.[5] Skoko et al.[6] concluded that hybrid propulsion systems in dredgers significantly reduce CO_2 emissions, fuel consumption, and operational costs, presenting an environmentally sustainable and economically advantageous alternative to conventional diesel engines. Adopting eco-driving principles by ship deck officers, such as optimizing routes for fuel efficiency and maintaining steady engine loads, is another effective operational measure.[5]

As no direct technology exists for purifying CO_2 emissions, international regulations focus on limiting fuel consumption The EU MRV Regulation (2015/757), implemented for ships calling at EU ports and the IMO Data Collection System (DCS) regulations introduced in 2019 represent significant steps toward reducing emissions. Additionally, tools such as the Energy Efficiency Design Index (EEDI) and the Ship Energy Efficiency Management Plan (SEEMP) have been developed to enhance energy efficiency and minimize CO2 emissions during ship design, operations and maintenance.[7–10]

Despite its high waste heat recovery potential, the cost of developing industrial-scale ORC (Organic Rankine Cycle) systems compatible with maritime applications has limited their adoption. Recent installations utilizing jacket water and exhaust gas waste heat have demonstrated the potential for annual fuel savings of 12.33% in port operations, alongside reductions in emissions.[11] Decision support systems, such as the one developed by[12] for optimizing routes and speeds, further highlight the potential for operational efficiency. Similarly, energy analyses of container ships have shown that cooling systems and exhaust gases account for approximately 65% of total energy consumption, underscoring the need for innovative energy management approaches.[13]

In this study, research was conducted on fuel consumption, a critical factor in voyage costs. Key factors affecting fuel consumption, including ship speed, loading conditions, sea and weather factors, suitable routes, fuel types, main engine specifications, propeller types and autopilot utilization, were identified and analyzed. Methods to enhance energy efficiency and reduce CO_2 and air pollutant emissions were also examined. Recommendations are provided based on applicable methods for various ship types, focusing on design, operational planning and maintenance practices. The Analytic Network Process (ANP), a Multi-Criteria Decision-Making (MCDM) method, was employed to determine sub-criteria weights, while the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used to rank the main criteria.

Literature review

Fuel consumption is a critical determinant of operational costs in maritime transportation and reducing it is essential for achieving both economic and environmental objectives. Vessel voyage optimization is influenced by numerous dynamic and complex factors, including fuel prices, charter rates and operating conditions.[14] As fuel oil consumption (FOC) constitutes over 25% of a vessel's overall operating costs, accurate forecasting and reliable prediction of related expenditures significantly enhance operational sustainability and profitability.[15] It is well-established that fuel consumption is directly proportional to speed; hence, reducing speed is a practical approach to decrease fuel use.[16] Kim et al.[17] found current measures inadequate for Carbon Intensity Indicator (CII) targets, emphasizing port delays and poor stakeholder communication, and recommended improved fuel management, biofuels, and Just-in-Time strategies (JIT). Ronen[18] highlighted that fuel costs account for approximately 75% of total operating expenses, making it imperative for shipping companies to monitor fuel efficiency. Additionally, Büker et al.[19] revealed that traditional positive displacement (PD) flow meters lose accuracy in measuring fuel consumption of low-viscosity fuels due to viscosity and inlet pressure. Their servo-controlled PD flow meter achieved under 2% error, offering a precise alternative for maritime fuel consumption measurement.

Bialystocki and Konovessis[1] emphasized that fuel consumption is influenced by draft, displacement, air force, hull and propeller conditions and weather. Stronger headwinds, for instance, significantly increase fuel consumption.

Operational factors such as daily running costs, weather and sea conditions, fuel prices, and port fees are often uncontrollable, while ship speed, cargo quantity and cargo type are manageable variables.[20] Efficient route and voyage planning, informed by updated information, can improve energy efficiency by up to 10%.[21] Moreover, voyage optimization techniques aim to minimize fuel consumption through precise trajectory and engine power adjustments based on weather conditions, while maintaining constraints such as ship motions and expected time of arrival.[22]

Alternative fuels have also gained attention as part of emission-reduction strategies. Very-Low Sulphur Fuel Oil (VLSFO), marine gas oil (MGO) and Liquefied Natural Gas (LNG) are increasingly utilized, with LNG offering reduced sulfur and carbon emissions despite challenges related to storage and supply logistics.[23,24] However, Zhang et al.[25] found switching cargo ships from heavy fuel oil (HFO) to diesel under low-sulfur regulations increased volatile organic compound (VOC) emissions by 48%, raising ozone (O_3) and secondary organic aerosol (SOA) formation potential.

Technological advancements such as trim optimization and hull cleaning have proven effective in enhancing energy efficiency. Jugović et al.[26] found optimizing fixed-pitch propellers using Metrascan 3D improved hydrodynamic performance and significantly reduced fuel consumption, meeting EU CO_2 standards cost-effectively. Reports by the IMO and DNV indicate that trim optimization can save between 4% and 15% of bunker fuel.[27] Hull surface roughness and propeller maintenance are equally critical; small adjustments in trim through ballast management can lead to fuel savings of up to 15%.[28]

Machine learning applications in fuel consumption modeling have also shown promise. Uyanık et al.[10] demonstrated that engine RPM, cylinder pressure and scavenge air significantly influence fuel efficiency. Additionally, Zhou et al.[29] developed a model for tanker fuel consumption prediction based on noon reports, highlighting the potential of data-driven approaches.

Speed optimization remains a widely studied area, with significant savings reported across various vessel types. For instance, Yuan and Nian[30] observed a 19% reduction in fuel consumption through a 10% speed decrease. However, Psaraftis and Kontovas[31] noted potential trade-offs, including prolonged voyage times, which could offset economic and environmental benefits. Sert and Bilgili[32] found that speed optimization is less feasible for container ships but more applicable to dry bulk carriers.

Operational methods such as diesel-electric power generation systems have also demonstrated efficiency improvements. Lundh et al.[33] reported fuel savings of 4%–6% on cruise ships utilizing these systems.

This study aims to contribute to the existing literature by investigating factors that influence fuel costs, such as speed, cargo status, sea and weather conditions, route optimization and fuel type, while highlighting the importance of emission reduction in maritime operations. Given the global need to address air pollution from shipping, which is a significant source of sulfur oxides (SOx), nitrogen oxides (NOx) and carbon dioxide (CO2) emissions, the study seeks to integrate fuel efficiency with environmental considerations. By employing the ANP method to determine the weights of sub-criteria and the DEMATEL method to rank the main criteria, the study intends to offer a comprehensive approach to fuel consumption management. This dual focus is not only meant to enhance the operational cost-effectiveness of ship voyages but also to contribute to the broader sustainability goals of the shipping industry. The findings are expected to assist shipping companies in optimizing voyage planning while reducing harmful emissions, thereby supporting the alignment of operational practices with global regulatory frameworks such as IMO 2020 and the Paris Agreement. The research is designed to improve upon previous methodologies by providing a structured decision-making framework through ranking and prioritization processes. Ultimately, the results aim to address a critical gap by connecting operational efficiency with sustainability objectives, offering maritime stakeholders practical strategies to reduce emissions and improve cost-effectiveness. This study aspires to provide new insights into the field by supporting the development of standardized fuel management strategies in the maritime industry.

Material and methodology

A hybrid technique combining the analytical network process (ANP) and the decision-making trial and evaluation laboratory (DEMATEL) was used to identify the most crucial factors influencing the best choice to ship fuel consumption alternative applications. Conventional evaluation techniques often use either the minimal cost or the maximum benefit as their only index of measuring criterion.[34] Furthermore, these methods might not be suitable for varied and increasingly complex decision-making situations. So, a hybrid MCDM technique using DEMATEL and ANP was employed to identify the best ship fuel consumption alternative applications decision selection for ships. First, the problem's formulation was developed, along with the primary goals and assessment clusters.

The factors that could be useful in figuring out the appropriate ship fuel consumption alternative applications criteria were assessed using the DEMATEL approach. Each node's crucial influence on the decision regarding the ship fuel consumption alternative applications criteria and the network effect was identified. Each node's crucial influence on the decision regarding ship fuel consumption alternative applications criteria and the network effect was identified. In the selection of decision of the ship fuel consumption alternative applications and the network effect, each node's crucial influence was identified. Based on pairwise comparisons of the total-relation matrix values $(D + R \text{ and } D - R)$, an initial direct-relation matrix was produced and using the DEMATEL approach, the criteria were grouped into a crucial relative graph. In order to determine the most important factors in choosing the appropriate ship fuel consumption alternative applications, it is required to describe the network structure of the clusters using the relative graph. The vertical axis of the digraph depicts the kind and direction of effect according to the analytical value of each criterion, while the horizontal axis of the digraph displays the strength of the most important elements. The inner relations between the two criteria can also be depicted by evaluating the results of the pairwise comparisons of the involved factors. It is necessary to first construct the network effect using DEMATEL before generating the objective super-matrix of ANP.

By describing the internal relationships between the set of criteria and getting the primary criterion, the DEMATEL technique is a step-by-step procedure for assessing the significance of the primary factor involved in the decision-making process.[35] The criteria supplied as digraphs in DEMATEL are used to build the cause-and-effect groups.[36–38] According to Tzeng et al.,[36] this method is commonly used to resolve complicated decision-making issues including causal connection analysis. According to the literature that is currently accessible[34,37,39,40] the DEMATEL approach was employed in this work. This technique's steps may be summed up as follows:

Step 1: The first direct-relation matrix is created in Step 1 by computing the average matrix that is required. A five-level comparison scale between "*0* and *4*" is created to apply the pairwise comparison of the related impacts of each criterion for quantification purposes. The objective is to gather quantifiable data on assessments that range from "*no influence*" to "*very high influence*." To compare the relationship impacts of each criterion pairwise for quantification purposes, a five-level comparison scale between "*0* and *4*" is devised. The goal is to gather quantifiable data on judgments with varying degrees of impact, from "*no influence*" to "*very high influence*."

Step 2: The initial direct-relation matrix's normalization approach is used. The DEMATEL method in this study uses the linear normalization approach. This method was selected due to its simplicity and effectiveness in ensuring that all values fall within a standardized range between 0 and 1, making the results comparable and interpretable. Linear normalization is widely recognized in the literature[35,36] as an appropriate method for handling direct-relation matrices in DEMATEL applications. This ensures consistency and reliability in the influence assessment process.

Step 3: Using the identity and direct-relation matrices, the total-relation matrix is calculated.

Step 4: To determine the causes and effects of each component over the whole network, the sum of the rows and columns in the total-relation matrix "***K***" is assessed. In this stage, the total of the matrix's rows and columns is expressed as *"D"* and *"R"* by the following equations:

$$\mathrm{K} = [k_{uy}]u, y = 1, 2, 3, \ldots\ldots\ldots\ldots n \tag{1}$$

$$\mathrm{D} = (D_u) = \left(\sum_{y=1}^{n} k_{uy}\right) \tag{2}$$

$$\mathrm{R} = (R_y) = \left(\sum_{u=1}^{n} k_{uy}\right) \tag{3}$$

where *"u"* and *"y"* stand for the overall influence sent from criterion *"y"* to the other criteria, *"K"* and *"D"* are the sum of each row in matrix *"K"* respectively. *"Ry"* is the total of the column that displays the effect that each of the other criteria in the matrix "K" has on the factor "u" The index indicating the intensity of influence transmitting and receiving is the sum of $(D + R)$. Additionally, if $(D - R)$ is positive, the factor's impact is sent to the other criteria and if (D − R) is negative, the other criteria's influence is received by the criterion.

Step 5: Ultimately, the user should pick a threshold value to eliminate certain minor variables in order to create a digraph of the pairwise expert evaluating procedure. In this investigation, the threshold value was determined by averaging the values of the matrix's *"K"* members. Therefore, the digraph only displays values greater than the threshold value. The *"D + R"* and *"D − R"* are mapped to create the digraph.

The other method in this study is the modified analytical hierarchy process (ANP) methodology. Due to the logical process involved, which can incorporate dependencies and feedback utilizing a hierarchical decision network[34,38] the ANP approach has garnered a wide user reaction in the scientific community. By estimating the weight of each cluster in the decision-making process, ANP may be used to evaluate the dependence and feedback rates for each cluster and the overall network.[38,41,42] Saaty,[43] offers to employ a super matrix, often known as the ANP technique in the literature, to solve the interdependency issue across several clusters. In the super matrix structure, each matrix element's weight is separately evaluated in a network where each matrix member has a relative impact over the others. The choice problem's priorities are determined using the super matrix approximation approach.

The ANP method suggested by Chen and Yu,[40] Saaty[43] and Saaty[44] has been applied in this work. The requirements for ship fuel consumption alternative applications were prioritized according to a step-by-step method. The network relation map was initially created using DEMATEL and after that, a new matrix known as the "cut total-influence matrix" was created by deriving the total influence matrix "K" and the threshold value. A super matrix was created by merging the normalized total influence matrix and the unweighted super matrix based on the relative influences of each criterion in the matrix structure after the cut-total-influence matrix was normalized. Finally, a stable super matrix was created by raising the super matrix's limit to a big enough power to determine the relative importance of each criterion.

In this study, the ANP methodology outlined by Chen and Yu,[40] Saaty[43,44], Ou Yang et al.[45] was followed. The process involved several sequential steps to determine the relative importance of the criteria influencing the selection of an ideal ship fuel consumption alternative applications.[38,42]

As the first step, a network relationship map was developed using the DEMATEL approach. Following this, the total influence matrix "K" was computed and the threshold value "α" was established. This led to the creation of an α-cut total-influence matrix. Afterward, the α-cut total-influence matrix was normalized, which allowed for the construction of a supermatrix. This supermatrix combined the normalized total-influence matrix with the unweighted supermatrix, reflecting the relative influences of the elements within the system.

The final step involved calculating the stable supermatrix by raising the supermatrix to a sufficiently high power. This iterative process provided the final priorities or weights for each criterion, which are essential for determining the most significant factors in the ship fuel consumption alternative applications criteria selection. In this study, the Super Decisions software was employed to implement the Analytic Network Process (ANP), enabling pairwise comparisons, weight calculations and the construction of the supermatrix. Additionally, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was conducted using MATLAB to analyze the causal relationships among the criteria. The selection of these software tools was based on their capability to handle complex multi-criteria decision-making (MCDM) frameworks, ensuring methodological rigor, consistency, and reliability in the analysis.

The case study of the ship fuel consumption alternative applications

In this case study, the ideal ship fuel consumption alternative was approached as a complex decision-making problem that necessitates an analytical framework grounded in expert knowledge. A panel of experts was assembled to evaluate the set of criteria and determine the most important ones by assessing the weight assigned to each criterion. A group of 21 experts, selected for their experience and expertise, participated in the evaluation process through pairwise comparison matrices. Detailed information regarding the composition of the expert panel is provided in Table 1. The selection of the expert team was based on professional background and industry experience, with particular emphasis on ship technical management, as this is highly relevant to the decision at hand. Consequently, the distribution of experts was not uniform across all professions, with a majority of the panel comprising ship technical managers. All quantitative data required for the DEMATEL and ANP analyses were derived from the expert evaluations, ensuring that the input data reflected industry expertise and practical knowledge.

All quantitative information utilized in DEMATEL and ANP computations was derived from the expert team's evaluations. The members of the expert team were picked based on their professional backgrounds and work history. As a result, the technical managers of the ship comprised the majority of the specialists. The criteria for selecting the ship fuel consumption alternative applications were developed in accordance with the and IMO Regulations as shown in Table 2. Environmental pollution and CO2 emissions, which have been on the agenda intensively in recent years, are solid basic components of IMO's control and implementation studies. The first step in increasing energy efficiency on ships is to analyzes and determines the current situation in energy efficiency. Thus, the areas where productivity will be increased can be determined more easily.[46] IMO has developed a module that allows member states to transfer fuel consumption data of ships. With this module, it seeks to reduce environmental pollution and control CO2 emissions, as well as providing energy efficiency on ships (IMO, 2018).

To address the variation in the expertise and educational levels of the selected 21 experts, a weighting system was implemented to assign different weights to the scores provided by each expert. Weights were determined based on factors such as professional experience, educational background and relevance of expertise to the maritime industry. Experienced experts with extensive professional backgrounds were assigned higher weights, while less experienced individuals were given lower weights. This approach ensures that the constructed initial impact matrix reflects the varying contributions of experts and enhances the accuracy of the scoring process. The weighted scoring methodology has been applied following recommendations in similar multi-criteria decision-making studies.[38,43] To address the variation in the expertise and educational levels of the selected 21 experts, a weighting system was implemented to assign different weights to the scores

Table 1. Expert group profile.

Expert	Educational status	Experience (Year)	Weight assigned (Based on expertise)
Chief officer	B.Sc.	6–9	0.8
Shipbuilding engineer	B.Sc.	3–6	0.7
Chief officer	B.Sc.	6–9	0.8
Academician	Ph.D.	2–3	0.6
Chief officer	B.Sc.	6–9	0.8
Academician	Ph.D.	15 and more	1
Academician	M.Sc.	1–2	0.5
Shipbuilding engineer	B.Sc.	1–2	0.5
Captain	B.Sc.	12–15	0.9
Captain	B.Sc.	12–15	0.9
Academician	Ph.D.	12–15	0.9
Academician	Ph.D.	9–12	0.8
Academician	Ph.D.	6–9	0.7
Chief officer	M.Sc.	6–9	0.8
Oceangoing watchkeeping engineer	B.Sc.	6–9	0.8
Oceangoing watchkeeping engineer	B.Sc.	2–3	0.6
Captain	B.Sc.	15 and more	1
Chief officer	B.Sc.	6–9	0.8
Academician	M.Sc.	9–12	0.8
Academician	Ph.D.	12–15	0.9
Shipbuilding engineer	B.Sc.	3–6	0.7
Total	*21 Person*		

provided by each expert. Weights were determined based on factors such as professional experience, educational background, and the relevance of expertise to the maritime industry. Experts with more extensive professional backgrounds were assigned higher weights, while those with less experience were given lower weights. This approach ensures that the constructed initial impact matrix reflects the varying contributions of experts, thus enhancing the accuracy of the scoring process. The weighted scoring methodology follows the recommendations of similar multi-criteria decision-making studies.[38,43] The weighting process is grounded in the Fuzzy DEMATEL and Fuzzy ANP methodologies, where participant responses are assigned weights based on their professional experience, role, and specialized knowledge. The following factors were considered when calculating these weights:

Years of experience in the maritime industry: A participant's years of relevant experience were directly translated into a weight using a predefined scale (e.g. 1–5 scale).
Professional role: Higher-ranking roles, such as shipmasters and senior engineers, were assigned higher weights due to their direct involvement in decision-making processes.
Specialized knowledge of fuel consumption practices: Participants with in-depth knowledge in this area received higher weights, which were evaluated through a survey-based assessment.

The resulting weights were incorporated into the fuzzy logic-based analyses, ensuring that the more experienced and knowledgeable participants had a greater influence on the final results. A detailed table showing the weights assigned to each participant based on these criteria is provided in Table 1.

By weighting participants' opinions in this manner, we aimed to mitigate potential biases while improving the credibility and reliability of the findings. These weighted results are explicitly reflected in the study's analysis, with the influence of each participant's opinion clearly demonstrated in the final decision-making process.

The results from each questionnaire were subsequently utilized to construct a network representation of the ideal ship fuel consumption alternative applications requirements. The expert team members were provided with a pairwise comparison scale ranging from "0 to 4" to assess the relative importance of each criterion. Each comparison was classified on a scale of "0" (no impact) to "4" (very high influence), reflecting varying degrees of influence among the criteria. To further clarify this process, the pairwise comparison matrix for Expert 1 is presented in Appendix 1. This matrix outlines the relative impacts of the eight criteria as evaluated by Expert 1. Subsequently, the average of the individual expert matrices was computed to generate the final aggregated "8×8" initial direct relational matrix, as shown in Table 3. Due to constraints on word count and page length, only the matrix for Expert 1 is included. However, it should be noted that the matrices from all individual experts were used to derive the final decision matrix, as detailed above.

To create the normalized form of the matrix, which was then utilized to construct the total-relation matrix, the normalization method was applied to the initial direct-relational matrix. Table 4 displays the

Table 2. Ship fuel consumption alternative applications selection criteria.

C1. Engine Operation Applications	C2. Maintenance and regulations	C3. Ship Usage, Personnel Impact	C4. Environmental Impacts and Voyage Status	C5. Propeller	C6. Technical Specifications and application	C7. Ship hull form (condition of the vessel)	C8. Stability
C1.1. Main engine type (diesel, turbocharger…)	**C2.1.** Hull cleaning/ contamination	**C3.1.** Port period	**C4.1.** Weather condition	**C5.1.** RPM	**C6.1.** Recovery from waste heat	**C7.1.** Form/design/ design/coefficients of the vessel	**C8.1.** Draft
C1.2. Fuel type (alternative fuels)	**C2.2.** Lube oil change intervals	**C3.2.** Suitable speed according to sea conditions	**C4.2.** Sea condition	**C5.2.** Cavitation	**C6.2.** Port electricity use	**C7.2.** vibration of the vessel	**C8.2.** Load status
C1.3. Engine maintenance	**C2.3.** Compliance with Energy Efficiency and Emission Regulations	**C3.3.** Effective use of autopilot	**C4.3.** Depth (such as shallow water effect)	**C5.3.** Diameter	**C6.3.** Construction of Lightweight Ships	**C7.3.** Roughness and damage (including broadside)	**C8.3.** Ballast condition
C1.4. Use of Fuel and Additives	**C2.4.** Energy Efficiency Design Index	**C3.4.** Suitable route	**C4.4.** Current	**C5.4.** Blade area	**C6.4.** Optimization of Ship Main Dimensions	**C7.4.** Vessel surface coating applications	**C8.4.** Appropriate Ship Trim (Trim-draft optimization)
C1.5. Load Optimization in Engine Operations	**C2.5.** Ship docking periods	**C3.5.** Personal experience	**C4.5.** Wind	**C5.5.** Wing section	**C6.5.** Air Bubble Lubrication Technique on the Bottom of the Boat		**C8.5**. Squat effect
C1.6. Machine and exhaust gas operating temperature averages	**C2.6.** DG management and Shaft Gen.	**C3.6.** Carried Load (Stiff, tender loads etc.)	**C.4.6.** Voyage type and durations (Canal, strait crossings, ice water, iron, laid up etc.)	**C5.6.** Number of wings	**C6.6.** Ship Stern Design		**C8.6.** Bank effect
	C2.7. Power Management Applications on Ships	**C3.7.** Voyage Planning according to sea and weather conditions	**C4.7.** Ship maneuver frequency and times	**C5.7.** Minimizing the Resistance Caused by Propeller Gaps in the Ship Hull			

Table 3. Direct initial matrix.

Criteria set	C1	C2	C3	C4	C5	C6	C7	C8
C1	0	0.314	0.214	0.184	0.143	0.220	0.124	0.128
C2	0.121	0	0.348	0.212	0.241	0.155	0.398	0.414
C3	0.374	0.164	0	0.129	0.214	0.265	0.186	0.208
C4	0.225	0.255	0.174	0	0.139	0.322	0.069	0.321
C5	0.314	0.241	0.245	0.351	0	0.412	0.255	0.152
C6	0.201	0.185	0.184	0.217	0.320	0	0.329	0.020
C7	0.161	0.141	0.201	0.280	0.314	0.208	0	0.247
C8	0.174	0.165	0.227	0.229	0.154	0.187	0.218	0

Table 4. Total-influential relation matrix K.

Criteria set	C1	C2	C3	C4	C5	C6	C7	C8	Ry
C1	0.544	0.374	0.354	0.517	0.391	0.110	0.541	0.511	3.342
C2	0.315	0.567	0.621	0.634	0.218	0.619	0.328	0.412	3.714
C3	0.520	0.417	0.507	0.700	0.517	0.315	0.565	0.719	4.260
C4	0.354	0.528	0.641	0.371	0.421	0.401	0.163	0.131	3.010
C5	0.223	0.377	0.307	0.251	0.638	0.555	0.246	0.211	2.170
C6	0.405	0.608	0.312	0.611	0.301	0.101	0.391	0.380	3.109
C7	0.234	0.278	0.368	0.531	0.200	0.562	0.411	0.254	2.838
C8	0.624	0.524	0.407	0.211	0.711	0.109	0.342	0.421	2.928
Du	3.219	3.673	3.517	3.826	2.759	2.772	2.987	2.618	-

Table 5. Sum of influences given and received on each criterion.

Criteria	Du + Ry	Du − Ry
C1	6.561	−0.123
C2	7.387	−0.041
C3	7.777	−0.743
C4	6.836	0.816
C5	4.929	0.589
C6	5.881	−0.337
C7	5.825	0.149
C8	5.546	−0.310

total-influential relation matrix. Table 4 shows the total of the impacts each element sent out and received. The values of "Du" and "Ry" were determined using equations (2) and (3). The outcomes of "Du" and "Ry" are crucial in assessing the internal relationships between several variables that might be effective in the selection of a ship fuel consumption alternative applications. An evaluation of these values clarifies the factors that are dominant in the decision network and those that are influenced by other factors.

An average score for matrix "K" was computed as a threshold value to omit some negligible values in the matrix and the result for the threshold value was set as 0,657 (Found according to 21 Experts). The sum of the influences sent and received by each factor is shown in Table 5. Criteria that stand as net causes or effects are depicted as a digraph in Table 2 to map the network relationships.

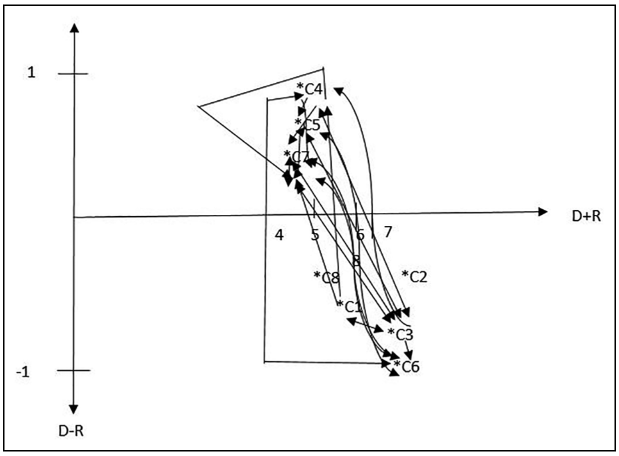

Figure 1. Diagraph map of the importance and relation level.

According to the results shown in Table 5, the *C3 (Ship Usage, Personnel Impact)* factor has the highest score *(7,777)* of $D + R$. Therefore, it can be accepted that it is the most important dimension of the case study, whereas *C5 (propeller)* criterion has been considered the least important in terms of "$Du + Ry$" values *(4, 929)*. To explain the cause-effect relationships and the importance of each factor involved in the ship fuel consumption alternative applications criteria assurance problem, a digraph with a horizontal axis $(D + R)$ representing the importance level and a vertical axis $(D - R)$ as for relations is given in Figure 1. Moreover, the final decision on ship fuel consumption alternative applications requirements assurance will depend on real numbers represented by "*Du*" and *"Ry"* values.

Table 6. Normalized total-influence matrix.

Criteria set	C1	C2	C3	C4	C5	C6	C7	C8
C1	0.701	0.089	0	0.511	0.098	0.487	0.218	0.138
C2	0.356	0.207	0.207	0.209	0.341	0.301	0.746	0.471
C3	0.178	0	0.631	0.181	0	0.610	0.610	0.621
C4	0.123	0.231	0.311	0.325	0.731	0.078	0.314	0.241
C5	0.457	0.513	0	0.404	0.569	0.247	0.014	0
C6	0	0.035	0.191	0.760	0	0.347	0.241	0.180
C7	0.341	0.210	0.034	0.587	0.451	0.502	0.541	0.430
C8	0.068	0.492	0.281	0.421	0.234	0.456	0.147	0

According to Figure 1, the *C4 (Environmental Impacts and Voyage Condition), C5 (propeller), C7 (Ship hull form condition of the vessel)* criteria were net causes, whereas the effect groups (receivers) with negative $(D-R)$ values were the *C1 (Engine Operation Applications), C2 (Maintenance and regulations), C3 (Ship Usage, Personnel Impact), C6 (Technical Specifications and application) and C8 (stability)* criteria set. Considering further the causal relationships map, it can be seen that the *C3 (Ship Usage, Personnel Impact), C2(Maintenance and regulations), C4 (Environmental Impacts and Voyage Condition)* and *C1(Engine Operation Applications)* criteria were the most important factors that should be considered deciding on the ideal ship fuel consumption alternative application. It was also clear from the digraph map that all factors were influenced or mutually interacted when deciding on the ideal the ideal ship fuel consumption alternative applications.

A normalized total-relation matrix was utilized as an input to the ANP method to determine the priorities that impact the requirements for the ideal ship fuel consumption alternative applications. It was unnecessary to determine the weight or significance of each criterion used in the decision-making process since the cluster network map of the components was mapped using the DEMATEL approach. Consequently, the whole influence matrix was calculated, as shown in Table 6.

To get quantitative data on the main criterion set with the most impact on the process, more research may be done on the digraph map of the network relation and importance level. Figure 1 made it clear that the criteria were the most important and should come first when choosing the ideal ship fuel consumption alternative applications. Therefore, the most influential criteria set that consists of *"C3" (Ship Usage, Personnel Impact), "C2" (Maintenance and regulations)* and *"C4" (Environmental Impacts and Voyage Condition)* main and related sub-criteria were analyzed by the ANP to decide on the weights or priorities. At this stage, the weighted super matrix was derived by combining the α-cut total-influence matrix and the unweighted super matrix. Finally, a resultant matrix with quantitative information on each criterion can be derived by raising the limit to sufficiently high power on the weighted super matrix, as shown in Appendix 2.

Results and discussion

The problem of low fuel consumption practices on ships was effectively addressed using a hybrid MCDM (Multi-Criteria Decision-Making) technique that integrates DEMATEL (Decision-Making Trial and Evaluation Laboratory) and ANP (Analytic Network Process). This approach provides decision-makers, ship masters and technical managers with insights into the critical factors influencing ship management decisions, enabling them to implement strategies for both economic and environmental benefits. By incorporating expert knowledge and quantitative data, the MCDM method facilitates the evaluation of complex operational scenarios. This methodology has been successfully applied in various maritime applications, including ship accident assessments,[42] port selection problems,[47,48] and shipping business processes.[49] The integrated DEMATEL and ANP approach, which is infrequently applied in maritime literature, has proven effective in identifying and ranking the critical criteria clusters related to fuel consumption.

As shown in Figure 2, which presents the super matrix results in a graphical format, the rankings of all criteria are provided, with the top three most influential sub-criteria identified as C3.2 (Suitable speed according to sea conditions), C3.7 (Voyage planning according to sea and weather conditions), and C2.3 (Compliance with Energy Efficiency and Emission Regulations). These findings underscore the significance of ship operation strategies, regulatory adherence, and environmental considerations in reducing fuel consumption and mitigating air pollution.

Compliance with sea conditions, represented by subcriterion C3.2, plays a pivotal role in optimizing fuel consumption by enhancing operational efficiency. When ship speed and route planning are carefully adjusted to align with prevailing sea and weather conditions, the result is smoother navigation, reduced resistance, and, consequently, minimized fuel consumption. Additionally, the expertise of shipmasters in adjusting operational parameters – such as speed and course – based on real-time sea and weather data is integral to improving fuel efficiency. This adaptation to dynamic environmental factors helps mitigate excessive fuel consumption caused by adverse conditions, such as high

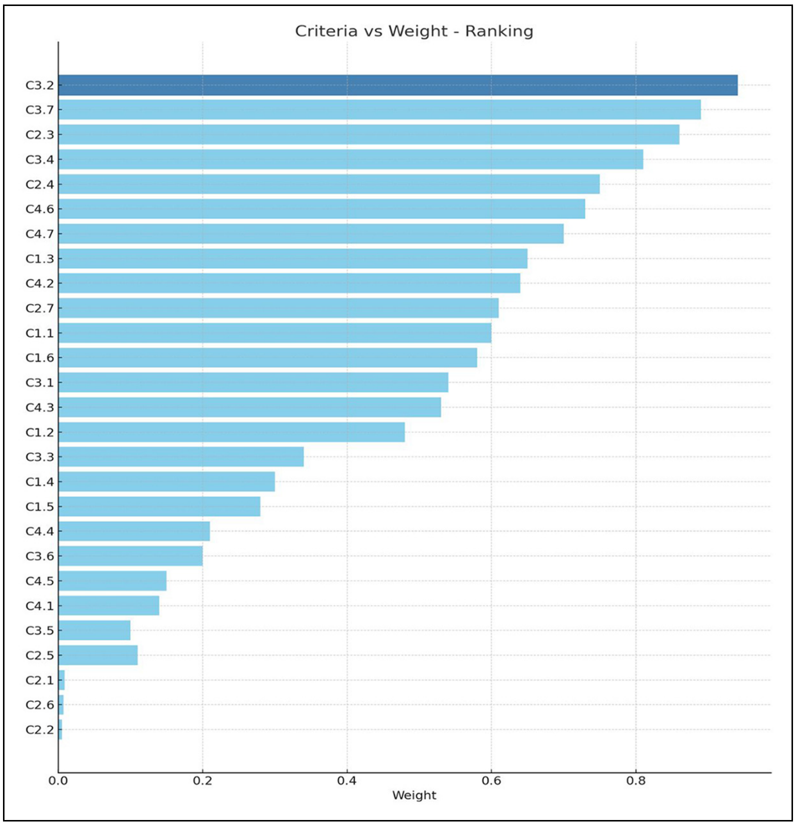

Figure 2. Super matrix with relative weights and ranking of criteria.

waves or strong winds, thereby enhancing overall operational performance.[50] In summary, aligning ship operations with prevailing sea conditions significantly reduces hydrodynamic resistance, which is the primary factor influencing engine power demand. Lower resistance directly results in reduced fuel consumption at a given speed. Therefore, compliance with sea conditions is not only operationally advantageous but also essential from both energy efficiency and emissions reduction perspectives.[50]

The maritime industry consumes approximately 4 million barrels of oil daily, contributing significantly to global greenhouse gas emissions, including CO2, SOx, and NOx.[46] Implementing fuel-efficient routing algorithms can lead to substantial reductions in fuel consumption and emissions, with an estimated daily savings of 50,000 barrels of oil, even at a modest 5% fuel savings rate. Similarly, in this study, the main criterion of Environmental Impacts and Voyage Status (C4) ranked third, while the Sea State (C4.2) sub-criterion emerged as the ninth most influential factor. These findings underscore the need for environmentally conscious decision-making in voyage planning to minimize both fuel consumption and emissions.

Although Ziylan[51] highlighted the potential of autopilot systems in reducing rudder-induced energy losses, human intervention remains necessary under adverse weather conditions or during critical maneuvers. In this study, while Ship Usage and Personnel Impact (C3) was identified as the most significant criterion, the effective use of autopilot was found to have minimal influence. This aligns with previous findings, suggesting that while automation aids efficiency, it must be complemented by human expertise to maximize benefits.

Hull maintenance also plays a vital role in fuel efficiency and emission reduction. Nassiraei et al.[52] reported that frequent hull cleaning is essential for maintaining fuel efficiency and minimizing CO2 emissions. However, despite being part of the Maintenance and Regulations (C2) criterion, which ranked second overall, hull cleaning itself did not exhibit a significant direct impact in this study. This indicates that while maintenance practices are crucial, their effectiveness depends on integration with other operational measures.

The results further highlight that ship-related factors, such as condition, maintenance practices, and compliance with energy efficiency regulations, are critical for sustainable ship operations. For example, compliance with the Energy Efficiency Design Index (EEDI) and other IMO regulations contributes to both economic efficiency and environmental sustainability by reducing CO2 emissions. Moreover, planned maintenance reduces the risk of failures, ensuring safer and more efficient navigation.[53]

In comparison to existing literature, this study's findings on fuel efficiency and emission reduction strategies are consistent with several recent studies. For example, the work of Özdemir et al.[54] on maritime fuel efficiency emphasizes the importance of operational strategies and technological innovations in reducing fuel consumption. Similarly, Zhang et al.[55] and Li et al.[56] have highlighted the role of voyage planning and regulatory compliance in optimizing fuel consumption across different vessel types. Moreover, the integration of DEMATEL and ANP, as seen in recent studies by Singh and Agarwal[57] and Kumar and Sharma,[58] has proven to be an effective methodology for identifying and evaluating the relative importance of criteria in multi-criteria decision-making processes. However, this study also identifies areas for future research. Although the methods analyzed are effective in general contexts, their applicability to different ship types and operational environments may vary. For example, certain fuel-saving strategies may not be feasible for larger vessels or specific types of cargo ships, which could involve higher operational costs due to necessary equipment modifications or additional crew training.[59]

While the study provides significant insights, certain limitations should be acknowledged to guide future research. Not all fuel-saving methods are universally applicable to all ship types. For instance, some strategies may require additional equipment or structural modifications, resulting in higher investment costs. Moreover, the effectiveness of these methods varies with operational contexts, such as ship size, voyage type, and environmental conditions.

To further enhance the impact of this research, future studies should focus on integrating life cycle assessments of ship operations to comprehensively evaluate their environmental footprints. The inclusion of alternative fuels, such as LNG and biofuels, should also be explored for their potential to further reduce greenhouse gas emissions. Addressing these aspects would enable the maritime industry to adopt more sustainable practices, aligning with global decarbonization goals and ensuring compliance with emerging international regulations.

Conclusion

In the field of maritime transportation, fuel consumption remains a dominant operational challenge, driving ongoing efforts to optimize fuel usage through innovative technologies and strategies. This study has examined the key factors influencing fuel consumption and identified the main criteria and sub-criteria through a hybrid decision-making methodology that integrates DEMATEL and ANP. By using these methods, critical decision-making factors were ranked, providing valuable insights into effective fuel consumption management.

The analysis revealed that operational decisions, particularly C3.2 (Comply with sea conditions, speed and ship master expertise) and C3.7 (Voyage planning according to sea and weather conditions), are the most significant contributors to fuel consumption reduction. This highlights the critical role of both human expertise and operational planning in achieving energy efficiency. Despite these valuable findings, several research gaps remain that warrant further investigation. Future studies should focus on conducting real-time data collection and long-term monitoring during actual voyages to assess fuel consumption patterns in diverse operational environments. Moreover, expanding the sample size to encompass a broader range of ship types, operational scenarios and geographic regions will help enhance the generalizability and robustness of the findings. Future research could also explore the potential of integrating emerging technologies – such as machine learning for voyage optimization, autonomous navigation systems and alternative fuel technologies (e.g. LNG, biofuels) – to further reduce fuel consumption and emissions. Additionally, the development of more advanced models that incorporate a combination of environmental, economic and operational data could improve the decision-making framework for maritime fuel consumption management. Another avenue for future research is the exploration of regulatory and economic frameworks that could incentivize the adoption of energy-efficient practices. Investigating the impact of global decarbonization targets, such as those set by the International Maritime Organization (IMO), on the maritime industry's fuel consumption strategies would provide insights into the feasibility of meeting long-term sustainability goals. It would also help address the financial barriers that shipping companies face when implementing energy-saving technologies. Finally, while this study emphasizes the importance of operational strategies, future work should also focus on the integration of these strategies into policy recommendations. Revising international standards and conventions to formalize energy-efficient practices in maritime operations could drive sector-wide adoption of fuel-saving measures, contributing to global emission reduction targets. Although the initial costs of adopting such practices may be significant, the long-term benefits in terms of operational cost reductions, lower emissions and compliance with international environmental standards will likely far outweigh these costs. In conclusion, this study provides a comprehensive framework for understanding the key factors influencing fuel consumption in the maritime industry. The findings underscore the importance of continued research and innovation in this area to develop sustainable, cost-effective solutions that align with the global push toward a more sustainable and low-emission maritime industry.

Credit author statement

Conceptualization, D., B. and Ü., Ö.; methodology, Ü.Ö., data curation, D, B. and D., Y.; writing—original draft preparation, D., B.; writing—review and editing, Ü., Ö. and D., Y. All authors have read and agreed to the published version of the manuscript.

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Appendix 1. Expert 1's pairwise comparison matrix.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
C1	0	3	2	0	1	0	2	1
C2	1	0	4	2	0	3	1	0
C3	2	1	0	3	0	2	1	2
C4	0	3	1	0	2	1	0	3
C5	1	0	2	1	0	0	2	1
C6	0	1	3	2	1	0	0	2
C7	1	2	1	2	3	1	0	1
C8	0	1	2	3	1	2	1	0

Appendix 2. The final super matrix with relative weight of each criterion (Note: The bold values represent the first 10 criteria with the highest weight).

Criteria set Weights and ranking	C3.2	C3.3	C3.4	C3.5	C3.6	C3.7	C2.1	C2.2	C2.3	C2.4	C2.5	C2.6	C2.7	C4.1	C4.2	C4.3	C4.4	C4.5	C4.6	C4.7	C1.1	C1.2	C1.3	C1.4	C1.5	C1.6
C3.1	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	**0.54**	**0.54**	**0.54**	**0.54**	**0.54**
C3.2 (1)	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**	**0.94**
C3.3	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	**0.34**	**0.34**	**0.34**	**0.34**	**0.34**
C3.4 (4)	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**	**0.81**
C3.5	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	**0.10**	**0.10**	**0.10**	**0.10**	**0.10**
C3.6	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	**0.20**	**0.20**	**0.20**	**0.20**	**0.20**
C3.7 (2)	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**	**0.89**
C2.1	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	**0.009**	**0.009**	**0.009**	**0.009**	**0.009**
C2.2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	**0.005**	**0.005**	**0.005**	**0.005**	**0.005**
C2.3 (3)	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**	**0.86**
C2.4 (5)	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**	**0.75**
C2.5	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	**0.11**	**0.11**	**0.11**	**0.11**	**0.11**
C2.6	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	**0.007**	**0.007**	**0.007**	**0.007**	**0.007**
C2.7 (10)	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**	**0.61**
C4.1	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	**0.14**	**0.14**	**0.14**	**0.14**	**0.14**
C4.2 (9)	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**	**0.64**
C4.3	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	**0.53**	**0.53**	**0.53**	**0.53**	**0.53**
C4.4	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	**0.21**	**0.21**	**0.21**	**0.21**	**0.21**
C4.5	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	**0.15**	**0.15**	**0.15**	**0.15**	**0.15**
C4.6 (6)	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**	**0.73**
C4.7 (7)	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**	**0.70**
C1.1	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	**0.60**	**0.60**	**0.60**	**0.60**	**0.60**
C1.2	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	**0.48**	**0.48**	**0.48**	**0.48**	**0.48**
C1.3 (8)	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**	**0.65**
C1.4	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	**0.30**	**0.30**	**0.30**	**0.30**	**0.30**
C1.5	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	**0.28**	**0.28**	**0.28**	**0.28**	**0.28**
C1.6	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58