JOURNAL OF ENGINEERING SCIENCES

Volume 10, Issue 1 (2023)

Javanbakht T. (2023). A novel automated decision-making process for analysis of ions and organic materials in drinking water. Journal of Engineering Sciences, Vol. 10(1), pp. H1-H7, doi: 10.21272/jes.2023.10(1).h1

A Novel Automated Decision-Making Process for Analysis of Ions and Organic Materials in Drinking Water

Javanbakht T.

Department of Computer Science, University of Quebec in Montreal,
201 President Kennedy St., Montreal, H2X 3Y7 Quebec, Canada

Article info:

Submitted:	December 5, 2022
Received in revised form:	February 6, 2023
Accepted for publication:	February 20, 2023
Available online:	February 24, 2023

***Corresponding email:**
javanbakht.taraneh@courrier.uqam.ca

Abstract. This paper applies a novel automated decision-making process with TOPSIS to analyze ions and organic materials in drinking water. The hypothesis was that the modified TOPSIS algorithm with the Łukasiewicz fuzzy disjunction would be appropriate to optimize the drinking water samples. The maximum output values were set to one to apply the fuzzy disjunction. The concentrations of ions and organic materials in the drinking water samples were considered from the values for naturally occurring chemicals that would be of health significance. Materials with positive effects on the body were considered profit criteria, whereas other ones with negative impacts on human health were considered cost criteria. The analysis of samples with unmodified TOPSIS showed that profit criteria having high concentrations and cost criteria having low concentrations had the dominant effects on the candidates' ranking. The modified TOPSIS showed that the candidates' ranking in the second analysis series was the same as in the first. However, the value of 1.0 for the fourth candidate's concentration of nitrite, which resulted from the fuzzy disjunction in the algorithm of the modified TOPSIS, was attributed to the confusion of the drinking water and undrinkable water categories. The optimization results for drinking water samples could be applied in science and engineering based on the concentrations of their ions and organic materials with the automated decision-making process for their distinction from undrinkable water.

Keywords: drinking water, automated decision-making process, health public, environment.

1 Introduction

Access to drinking water in the environment is a key factor for human survival. The lack of this material in many regions has searched for drinking water a first-order task. For this purpose, many industries produce large-scale drinking water each year to overcome this challenge. However, diseases due to drinking polluted water cause more than 1 million deaths per year [1]. Therefore, the distinction and analysis of drinking water are crucial processes. This is a remaining need to search for water on the planets with primordial atmosphere [2-4]. The already applied approach is based on the registration of several photos obtained by satellites and their analysis by humans on Earth. At this level, all the tasks of gathering and analyzing the data are carried out by humans. However, the environmental conditions where drinking water would be searched would not always be appropriate for humans because of the lack of atmosphere, polluted environment, and extreme temperatures. Therefore, developing an automated decision-making process that distinguishes drinking water from undrinkable water and performs appropriate analysis and optimization is urgently needed.

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method with many applications in science and engineering [5-9]. This method ranks the candidates based on their distances from ideal solutions and closeness coefficients [10-14].

The characteristics of drinking water, such as its total dissolved solids, hardness, electrical conductivity, and cost, depend on the concentration of its ions [15-18]. Previous work presented the analysis of drinking water and undrinkable samples according to these characteristics with TOPSIS [7]. In the present paper, this method has been used to analyze the concentrations of ions with a new perspective for science and environmental applications. For this purpose, the modified version of the TOPSIS method in a recently developed software has been used to optimize and rank candidates.

Appropriate amounts of minerals in drinking water are essential for human health. Calcium is essential as the extracellular mineral forms different skeleton parts, such as teeth and bones [19]. Magnesium has several functions, such as helping the muscle and nervous system and binding to targets in enzymatic reactions [20]. Boron is essential for bone and central nervous system growth, hormone regulation, and reducing the risk of cancer, arthritis, and heart disease symptoms. It also positively accelerates wound healing and reduces pain in gynecological diseases and kidney stones by decreasing cytokines [21]. Copper has several roles in the body, such as storing calcium in bones and repairing or building connective tissues [22]. Chlorine is converted to chloride in the body. Sodium and chloride are the principal cation and anions of the body, respectively [23]. These ions maintain an equilibrated sodium balance to maintain body volume and blood pressure system and regulate blood pressure [23, 24]. Therefore, these minerals are considered in the current work as profit criteria for the analysis with unmodified and modified TOPSIS methods. It has been shown that nitrite consumption harms human health, leads to methemoglobinemia, and increases cancer incidence by promoting the formation of potentially carcinogenic nitrosamines [25, 26]. Hence, this ion was considered a cost criterion for this investigation with TOPSIS.

This paper is aimed to analyze and optimize the drinking water samples according to the concentrations of their ions using the unmodified and modified TOPSIS methods, this second algorithm for performing an automated decision-making process. Three tasks have been performed with the developed software: 1. optimization of drinking water samples with unmodified TOPSIS, 2. modification of TOPSIS with the Łukasiewicz fuzzy disjunction for performing automated decision making, 3. optimization of drinking water samples with modified TOPSIS for their analysis and optimization.

The application of an automated decision-making process for detecting and analyzing ions in drinking water samples for their distinction from undrinkable water and their optimization has not been performed yet. The current research results on these issues can be applied in science and engineering.

2 Research Methodology

The standard concentrations of ions in drinking water were considered from the World Health Organization (WHO) guideline for naturally occurring chemicals, according to which these concentrations would be of health significance.

The concentrations of the ions and organic materials for health significance in the standard drinking water sample, which was the first sample or candidate indicated as C_1 in the TOPSIS matrices, would be as below: calcium (80 mg/L), magnesium (60 mg/L), boron (2.4 mg/L), copper (2 mg/L), sodium (50 mg/L), chlorine (5 mg/L), nitrite (3 mg/L), 1,2-dichlorobenzene (1 mg/L), monochloramine (2 mg/L), dichloroisocyanurate (40 mg/L), and toluene (1 mg/L). The second, third, and fourth samples were indicated as C_2, C_3, and C_4, respectively. Their ions and organic materials concentrations were proportional to the first candidate's.

The TOPSIS code in Python presented on GitHub was used to analyze and optimize candidates as described previously [8, 9, 27].

The ions and organic materials determined the characteristics of drinking water samples, such as hardness, turbidity, etc. As the analysis of their concentrations was the aim of this paper, they were considered as criteria. Their concentration values were divided by 100 to adjust them between 0.0 and 1.0 and make them similar to fuzzy membership degrees for their use in the TOPSIS method.

The modified TOPSIS, including the Łukasiewicz fuzzy disjunction, was used in this paper, and this method was described previously [8]. The data analysis with the modified algorithm considered the members of drinking and undrinkable water categories. The category confusion due to humans' inappropriate consideration of the criteria that led to the inconsistency of their epistemic beliefs was analyzed as explained previously [8, 28].

The maximum value of 1.0, according to the Łukasiewicz fuzzy disjunction, was observed in the evaluation matrix in the output of TOPSIS [28].

3 Results

The first series of results were obtained with the unmodified TOPSIS algorithm.

Tables 1-2 show matrices of the triangular fuzzy data corresponding to the concentrations of ions and organic materials in the water samples and their average values.

Table 1 – Matrix of triangular fuzzy data for different water samples

Candidates/Criteria	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1	0.7, 0.8, 0.9	0.5, 0.6, 0.7	0.01, 0.02, 0.03	0.01, 0.02, 0.03	0.4, 0.5, 0.6	0.04, 0.05, 0.06	0.02, 0.03, 0.04
C_2	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.4, 0.5, 0.6	0.4, 0.5, 0.6	0.05, 0.06, 0.07
C_3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.3, 0.4, 0.5	0.3, 0.4, 0.5	0.0, 0.1, 0.2	0.0, 0.1, 0.2	0.05, 0.06, 0.07
C_4	0.3, 0.4, 0.5	0.2, 0.3, 0.4	0.3, 0.4, 0.5	0.7, 0.8, 0.9	0.0, 0.1, 0.2	0.0, 0.1, 0.2	0.00, 0.01, 0.02

Table 2 – Matrix of the mean values of triangular fuzzy data for different water samples

Candidates/Criteria	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1	0.8	0.6	0.02	0.02	0.5	0.05	0.03
C_2	0.2	0.2	0.20	0.20	0.5	0.50	0.06
C_3	0.2	0.2	0.40	0.40	0.1	0.10	0.06
C_4	0.4	0.3	0.40	0.80	0.1	0.10	0.01

Tables 3-4 show the weight values applied for each criterion and the criteria matrix of different water samples, respectively.

Table 3 – Weight values applied for each criterion of different water samples

Alternatives/Values	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1–C_4	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Table 4 – Criteria matrix for different water samples

Alternatives/Values	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1–C_4	True	True	True	True	True	True	False

Materials with positive effects on human health were considered profit criteria, whereas those with negative effects were considered cost criteria. Therefore, the term "true" was considered for all the criteria. The exception is those for which "false" was in the criteria matrix in TOPSIS.

Table 5 represents the distances from the best and worst alternatives (di* and di-), the similarity coefficients (CC_i), and the ranking of water samples.

Table 5 – The distances from the best and worst alternatives, similarity coefficients, and ranking of different water samples

Candidates	d_i^*	d_i^-	CC_i	Ranking
C_1	0.1978	0.1518	0.4342	4
C_2	0.1782	0.1551	0.4655	2
C_3	0.2071	0.1090	0.3448	1
C_4	0.1595	0.1751	0.5234	3

As shown in Tables 2, 5, sodium, chlorine, boron, and copper, having high concentrations, and nitrite having low concentrations, had the dominant effects on the candidates' ranking. Therefore, the fourth candidate, C_4, was ranked in a position better than the other candidates. Moreover, higher concentrations of boron, copper, and chlorine for the second candidate compared with those for the first candidate showed their effect on the preference of candidate C_2 to candidate C_1 in the ranking. The third candidate, C_3, having lower concentrations of calcium, magnesium, and sodium and a higher concentration of nitrite, was ranked fourth.

In the second series of this study, the modified TOPSIS algorithm, with the Łukasiewicz fuzzy disjunction, was used for performing the automated decision-making process, which allowed the appearance of the maximum value of 1.0 in the output.

These modifications were considered in the second series of this analysis: 1. The concentration of the nitrite ion in the fourth candidate was high (0.5 mg/L in place of 0.03 mg/L). 2. Nitrite was considered as a profit criterion like the other ions by the individual. Therefore, the term "true" was considered for all the criteria in the criteria matrix of TOPSIS. This was due to the confusion of the drinking and undrinkable water categories by the individual leading to the appearance of the value of 1.0 for the nitrite concentration for the last water sample (candidate C_4). Also, this is due to the application of the Łukasiewicz fuzzy disjunction representing the high concentration of this ion and that of the candidate of the undrinkable water category. As the candidates' membership degrees in this analysis were the concentrations of ions and organic materials in water samples, the addition of the concentration of nitrite for candidate C_4 with that of the undrinkable water sample from the undrinkable water category would be considered according to this fuzzy disjunction (0.5 mg/L + 0.5 mg/L = 1.0 mg/L). As the maximum value of concentrations in the modified TOPSIS algorithm was set to 1.0, this value appeared in the output of the modified TOPSIS.

The two modifications described in the second series of analyses are shown in Tables 6-7.

Table 6 – Matrix of the mean values of triangular fuzzy data for different water samples

Candidates/Criteria	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1	0.8	0.6	0.02	0.02	0.5	0.05	0.03
C_2	0.2	0.2	0.2	0.2	0.5	0.5	0.06
C_3	0.2	0.2	0.4	0.4	0.1	0.1	0.06
C_4	0.4	0.3	0.4	0.8	0.1	0.1	1.0

Table 7 – Criteria matrix for different water samples

Alternatives/Values	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite
C_1–C_4	True	True	True	True	True	True	True

The weight values of 0.5 were applied for each criterion of water samples like the ones applied in the first series of analyses.

Tables 7-8 show the distances from the best and worst alternatives, the similarity coefficients, and the ranking of different water samples.

Table 8 – The distances from the best and worst alternatives, similarity coefficients, and ranking of different water samples

Candidates	d_i^*	d_i^-	CC_i	Ranking
C_1	0.2391	0.1442	0.3762	4
C_2	0.2083	0.1552	0.4269	2
C_3	0.2335	0.1090	0.3183	1
C_4	0.1595	0.2086	0.5667	3

The comparison of the rankings in the two series of analyses shows the same ranks for the candidates. However, the value of 1.0 appeared in the output of TOPSIS in the second series of analyses. The first rank for the fourth candidate (C_4) would not be accepted due to the individual's mistake of considering nitrite in this water sample as a profit criterion, as this ion should have been considered as a cost criterion, as explained in this paper. This candidate would be considered drinking water in the first analysis series, whereas it would be considered undrinkable water in the second.

Boron and copper with excessive doses are harmful to human health and biological systems [29, 30]. Therefore, these ions were considered cost criteria in the third analysis series. Moreover, some organic materials, such as 1, 2-dichlorobenzene, monochloramine, dichloroisocyanurate, and toluene, as cost criteria were also added to the entry data matrix, and their concentrations appeared in the evaluation matrix of TOPSIS.

Table 9 shows the matrix of the mean values of triangular fuzzy data for different water samples.

Table 10 shows the weight values matrix applied for each water sample criterion.

Table 11 shows the criteria for drinking water samples.

Table 9 – Matrix of the mean values of triangular fuzzy data for different water samples

Candidates/ Criteria	Calcium	Magnesium	Boron	Copper	Sodium	Chlorine	Nitrite	1, 2-Dichloro-benzene	Monochlo-ramine	Dichloro-isocyanurate	Toluene
C_1	0.8	0.6	0.2	0.2	0.5	0.05	0.03	0.01	0.02	0.4	0.01
C_2	0.2	0.2	0.2	0.2	0.5	0.5	0.06	0.02	0.04	0.1	0.02
C_3	0.2	0.2	0.4	0.4	0.1	0.1	0.06	0.03	0.04	0.1	0.02
C_4	0.4	0.3	0.4	0.8	0.1	0.1	0.01	0.01	0.02	0.2	0.04

Table 10 – Weight values applied for each criterion of different water samples

Alternatives/ Values	Cal-cium	Magne-sium	Bo-ron	Cop-per	So-dium	Chlo-rine	Nit-rite	1, 2-Dichlo-robenzene	Monochlo-ramine	Dichloro-isocyanurate	Tolu-ene	1, 2-Dichloro-benzene
C_1–C_4	0.5	0.5	0.1	0.1	0.5	0.5	0.1	0.1	0.1	0.1	0.1	0.1

Table 11 – Criteria matrix for different water samples

Alternatives/ Values	Calcium	Magnesium	Boron	Copper	Sodium	Chroine	Nitrite	1, 2-Dichlo-robenzene	Monochlo-ramine	Dichloro-isocyanurate	Toluene
C_1–C_4	True	True	False	False	True	True	False	False	False	False	False

Table 12 shows the distances from the best and worst alternatives, the similarity coefficients, and the ranking of different water samples.

Table 12 – The distances from the best and worst alternatives, similarity coefficients, and ranking of different water samples

Candidates	d_i^*	d_i^-	CC_i	Ranking
C_1	0.1616	0.1918	0.5427	2
C_2	0.1584	0.1939	0.5504	1
C_3	0.2372	0.0367	0.1339	4
C_4	0.2098	0.0608	0.2246	3

As shown in Table 12, the water samples' ranking was modified due to adding organic materials and considering boron and copper as cost criteria. Comparing the obtained results showed that candidate 4 was replaced with candidate 2 as the best candidate in the third analysis series. Moreover, candidate 2 was replaced with candidate 1 and candidate 1 with candidate 4. The rank of candidate 3 did not change in both analysis. These results showed the importance of considering criteria in analyzing candidates with TOPSIS. The presence of the ions and organic materials considered as cost criteria could affect drinking water quality. Their ranking with this method has been helpful for their comparison with the samples without organic materials.

Recently, the TOPSIS method modified by incorporating the Łukasiewicz fuzzy disjunction in a new software has shown its efficacy in providing a novel automated water analysis decision-making process [7]. The current work presents the results of the analysis of drinking water samples based on the concentrations of their ions and organic materials. These works are the first step required for a perspective change in the search for drinking water. The results of these investigations can be used in the next generation of robots helping them distinguish the confusion of the categories of drinking water and undrinkable water with the appearance of 1.0 in the output of TOPSIS.

4 Discussion

The proposed detection and analysis procedure proposed a new insight for the perspective change in science and engineering, which could help robots become independent of humans for predicting, detecting, and analyzing the target category, which was that of drinking water in this study. Therefore, their performance could be done independently from humans. In other words, the application of the proposed new software by robots, instead of the organizations' procedure of taking photos from other planets and analyzing them by humans, can provide automated detection and analysis of this important material in environmental conditions. This would not be appropriate for humans because of the lack of atmosphere, polluted environment, and extreme temperatures. Further investigations would be required to implement this software in the next generation of robots to search for drinking water on other planets.

TOPSIS is a decision-making algorithm. As categorization is the central process for decision-making in humans and it is before learning, in a perspective change for artificial intelligence, decision-making processes applying algorithms such as TOPSIS, including the issues of categorization, a cognitive disorder due to inconsistency in epistemic beliefs should be considered before machine learning. In other words, these issues should be implemented in new software in combination with this last method to advance science and engineering.

Previously, the properties of different nanomaterials [31-35], biomaterials [36-40], and construction materials [41, 42] were investigated for diverse applications in science and engineering. It has been revealed that nanoparticles [43, 44], polymers [45-48], and nanocomposites [49] would be used for water treatment, and more investigations could be performed for this application.

During recent years, TOPSIS has been used for the optimization and analysis of polymers [50-53], nanomaterials [54-56], and machine process or operation parameters [57-60]. More investigations would be required to develop this algorithm for the manufacturing optimization of materials and their preparation procedures for environmental studies.

5 Conclusions

The search for water in difficult environmental conditions is essential for human survival, for which a new perspective has been proposed in this paper.

The drinking water analysis in this work aimed to demonstrate and explain how to apply the automated decision-making process with modified TOPSIS in comparison with the unmodified algorithm for the prediction, analysis, and optimization of this material based on the concentrations of its ions and organic materials. The modified TOPSIS method was obtained using the Łukasiewicz fuzzy disjunction in this algorithm, according to which the maximum values of the membership degrees, the concentrations of ions, and organic materials of drinking and undrinkable water samples, were set to one. It was observed that the candidates' distances from the best and worst alternatives and similarity coefficients were different with the unmodified and modified algorithms. However, the same rankings were obtained for both of them. Moreover, the appearance of the value of 1.0 in the output of the modified algorithm corresponded to an individual's confusion about drinking and undrinkable water categories. This could be due to the inconsistency in his epistemic beliefs. The analysis revealed that adding organic materials to the list of the water's content led to a change in the candidates' ranking. With the new application of the TOPSIS method for predicting, detecting, and analyzing drinking water, this investigation could be applied in sciences and engineering.

References

1. Dawood, D. H., Sanad, M. I. (2014). Determination of ions (anion and cation) by ion chromatography in drinking water Talkha territory and some its villages, Dakahlia, Egypet, *J. Agric. Chem. and Biotechn.*, Vol. 5(9), pp. 215-226. DOI: 10.21608/jacb.2014.49898
2. Bell, J. F. (2010). Water on planets. *Highlights of Astronomy*, Vol. 15, pp. 29-44. DOI: 10.1017/S1743921310008161
3. Hubbard, G. S., et al. (2002). Following the water, the new program for Mars exploration. *Acta Astronautica*, Vol. 51(1-9), pp. 337-50. DOI: 10.1016/s0094-5765(02)00067-x
4. Nair, C. P. R., Unnikrishnan, V. (2020). Stability of the liquid water phase on Mars: A thermodynamic analysis considering Martian atmospheric conditions and perchlorate brine solutions. *ACS Omega*, Vol. 5(16), pp. 9391-9397. DOI: 10.1021/acsomega.0c00444
5. Hanine, M., et al. (2016). Application of an integrated multi-criteria decision making AHP-TOPSIS methodology for ETL software selection. *Springerplus*, Vol. 5, 263. DOI: 10.1186/s40064-016-1888-z
6. Azhar, N. A., et al. (2021). Multi-criteria decision making: A systematic review. *Recent Advances in Electrical & Electronic Engineering*, Vol. 14(8), pp. 779-801. DOI: 10.2174/2352096514666211029112443
7. Javanbakht, T. (2022). Automated decision-making with TOPSIS for water analysis. *Journal of Engineering Sciences*, Vol. 9(1), pp. H19-H24. DOI: 10.21272/jes.2022.9(1).h3
8. Javanbakht, T. (2022). Optimization of physical instruments' characteristics with TOPSIS, *Ukrainian Journal of Mechanical Engineering and Materials Science*, Vol. 8(3), pp. 1-9. DOI: 10.23939/ujmems2022.03.001
9. Javanbakht, T., Chakravorty, S. (2022). Prediction of human behavior with TOPSIS. *Journal of Fuzzy Extension and Applications*, Vol. 3, pp. 109-125. DOI: 10.22105/jfea.2022.326185.1197
10. Alguliyev, R., et al. (2020). Modified fuzzy TOPSIS + TFNs ranking model for candidate selection using the qualifying criteria. *Soft Computing*, Vol. 24(1), 681-695. DOI: 10.1007/s00500-019-04521-2
11. Varnamkhasti, M. J., et al. (2020). A new index for TOPSIS based on relative distance to best and worst points. *International Journal of Information Technology and Decision Making*, Vol. 16(03), pp. 695-719. DOI: 10.1142/S0219622020500145
12. Jumarni, R. F., Zamri, N. (2018). An integration of fuzzy TOPSIS and fuzzy logic for multi-criteria decision making problems. *Int. J. Eng. Tech.*, Vol. 7(2), pp. 102-106. DOI: 10.14419/ijet.v7i2.15.11362
13. Indahingwati, A., et al. (2018). Comparison analysis of TOPSIS and fuzzy logic methods on fertilizer selection. *International Journal of Engineering and Technology*, Vol. 7(2.3), pp. 109-114. DOI: 10.14419/ijet.v7i2.3.12630
14. Sadabadi, S. A., et al. (2020). A new index for TOPSIS based on relative distance to best ans worst points. *International Journal of Information Technology and Decision Making*, Vol. 19(3), pp. 695-719. DOI: 10.1142/S0219622020500145
15. Clark, R. M., Goddard, H. (1977). Cost and quality of water supply. *Journal of Americal Water Works Associations*, Vol. 69(1), pp. 13-15. DOI: 10.1002/j.1551-8833.1977.tb02533.x
16. Büker, O., Stolt, K., Kroner, C., et al. (2021). Investigations on the influence of total water hardness and pH value on the measurement accuracy of domestic cold water meters. *Water*, Vol. 13, 2701. DOI: 10.3390/w13192701

17. Xianhong, Y., Shijun, L., et al. (2021). Application analysis of conductivity in drinking water quality analysis, *International Energy, Environment and Water Resources Conference*. *IOP Publishing*, Vol. 784, 012028. DOI: 10.1088/1755-1315/784/1/012028
18. Thirumalini, S., Joseph, K. (2009). Correlation between electrical conductivity and total dissolved solids in natural waters. *Malaysian J. .Sci.*, Vol. 28(1), pp. 55-61. DOI: 10.22452/mjs.vol28no1.7
19. Aggarwal, P., et al. (2016). Role of calcium in human body – A review. *Bhavnagar University's Journal of Dentistry*, Vol. 6(1), pp. 30-34.
20. Khali, S., Alharthi, S. (2020). On-selective membrane sensor for magnesium determination in pharmaceutical formulations. *Int. J. Electrochem. Sci.*, Vol. 15, pp. 9223-9232. DOI: 10.20964/2020.09.39
21. Nikkhah, S., Naghii, M. R. (2019). Medicinal properties of boron supplementation on the prevention and treatment of diseases: A systematic review. *Complementary Medicine Journal*, Vol. 9(3), pp. 3760-3779.
22. Ali, S. F. A., et al. (2012). Determination of copper concentration in human blood serum by using flame atomic absorption spectroscopy (FAAS). *International Conference on Chemical Engineering and Pharmaceutical Sciences*, pp. 140-142, 2012.
23. Walker, W. F., Jonhston, I. (1971). *Water and Electrolyte Metabolism.* The Metabolic Basis of Surgical Care, *Elsevier, Netherlands.*
24. Burnier, M., et al. (2015). Salt, blood pressure and cardiovascular risk: what is the most adequate preventive strategy? A Swiss perspective. *Front. Physiol.*, Vol. 6, 227. DOI: 10.3389/fphys.2015.00227
25. Wang, Z., Shao, Y. (2018). Effects of microbial diversity on nitrite concentration in *pao cai*, a naturally fermented cabbage product from China. *Food Microbiology*, Vol. 72, pp. 185-192.
26. Lundberg, J. O., et al. (2018). Metabolic effects of dietary nitrate in health and disease. *Cell Metabolism*, Vol. 28(1), pp. 9-22.
27. Javanbakht, T. (2022). Analysis of nanoparticles characteristics with TOPSIS for their manufacture optimization. *Journal of Engineering Sciences*, Vol. 9(2), pp. C1-C8. DOI: 10.21272/jes.2022.9(2).c1
28. Javanbakht, T. (2022). *Modélisation et Traitement Informatique de L'inconsistance des Croyances Épistémiques*. PhD Thesis, University of Quebec in Montreal, Canada.
29. Tu, K. L., Nghiem, L. D., Chivas, A. R. (2010). Boron removal by reverse osmosis membranes in seawater desalination applications. *Separat. Purif, Technol.*, Vol. 75, pp. 87-101. DOI: 10.1016/j.seppur.2010.07.021
30. Jabłońska, B., et al. (2019). Natural and chemically modified post-mining clays – Structural and surface properties and preliminary tests on copper sorption. *Minerals*, Vol. 9, 704. DOI: 10.3390/min9110704
31. Javanbakht, T., Hadian, H., Wilkinson, K. J. (2020). Comparative study of physicochemical properties and antibiofilm activity of graphene oxide nanoribbons. *Journal of Engineering Sciences*, Vol. 7(1), pp. C1-C8. DOI: 10.21272/jes.2020.7(1).c1
32. Javanbakht, T. (2021). Investigation of rheological properties of graphene oxide and its nanocomposite with polyvinyl alcohol. *Ukrainian Journal of Mechanical Engineering and Materials Science*, Vol. 7, pp. 23-32. DOI: 10.23939/ujmems2021.01-02.023
33. Javanbakht, T., David, E. (2020). Rheological and physical properties of a nanocomposite of graphene oxide nanoribbons with polyvinyl alcohol. *Journal of Thermoplastic Composite Matererials*, Vol. 35(5), 0892705720912767. DOI: 10.1177/089270572091276
34. Javanbakht, T., Laurent, S., Stanicki, D. and Salzmann, I. (2021). Rheological properties of superparamagnetic iron oxide nanoparticles. *Journal of Engineering Sciences*, Vol. 8, pp. C29-C37. DOI: 10.21272/jes.2021.8(1).c4
35. Javanbakht, T., Laurent, S., Stanicki, D., Frenette, M. (2020). Correlation between physicochemical properties of superparamagnetic iron oxide nanoparticles and their reactivity with hydrogen peroxide. *Can. J. Chem.*, Vol. 98, pp. 601-608. DOI: 10.1139/cjc-2020-0087
36. Ghane-Motlagh, B., Javanbakht, T., et al. (2016). Physicochemical properties of peptide-coated microelectrode arrays and their *in vitro* effects on neuroblast cells, *Mat. Sci. Eng. C*, Vol. 68, pp. 642-650. DOI: 10.1016/j.msec.2016.06.045
37. Javanbakht, T., Ghane-Motlagh, B., Sawan, M. (2020). Comparative study of antibiofilm activity and physicochemical properties of microelectrode arrays. *Microelectronic Engineering*, Vol. 229, 111305. DOI: 10.1016/j.mee.2020.111305
38. Dimitriadis, E. K., Horkay, F., Maresca, J., Kachar, B., Chadwick, R. S. (2002). Determination of elastic moduli of thinlayers of soft material using the atomic force microscope. *Biophysical Journal*, Vol. 82(5), pp. 2798-2810.
39. Javanbakht, T. Sokolowski, W. (2015). Thiol-ene/acrylate systems for biomedical shape-memory polymers. *Shape Memory Polymers for Biomedical Applications*, Vol. 8, pp. 157-166. DOI: 10.1016/B978-0-85709-698-2.00008-8
40. Javanbakht, T., Laurent, S., Stanicki, D., David, E. (2019). Related physicochemical, rheological, and dielectric properties of nanocomposites of superparamagnetic iron oxide nanoparticles with polyethyleneglycol. *J. App. Polym. Sci.*, Vol. 136, pp. 48280-48290. DOI: 10.1002/app.48280
41. Kuzmin, S. A., Egorova, A. D., Krasilnikov, D. A., Emelianov, Z. V. (2019). Durability of construction materials modified by polymeric additives. *Procedia Structural Integrity*, Vol. 20, pp. 278-283. DOI: 10.1016/j.prostr.2019.12.152
42. Djavanbakht, T., et al. (2000). Effets d'un chauffage thermique sur les performances de miroirs multicouches Mo/Si, Mo/C et Ni/C pour le rayonnement X mou. *Journal de Physique IV*, Vol. 10, pp. 281-287. DOI: 10.1051/jp4:20001031
43. Fiorati, A., et al. (2020). Silver nanoparticles for water pollution monitoring and treatments: Ecosafety challenge and cellulose-based hybrids solution. *Polym.*, Vol. 12(8), 1635. DOI: 10.3390/polym12081635
44. Nagar, A., Pradeep, T. (2021). Clean water through nanotechnology: Needs, gaps, and fulfillment. *ACS Nano*, Vol. 14(6), pp. 6420-6435. DOI: 10.1021/acsnano.9b01730
45. Serajuddin, et al. (2020). Application of a polymer in drinking water treatment: A case study. *5th Intern. Conf. Civil Eng. Sustain. Dev.*, Vol. ICCESD-2020-4407, pp. 1-12.
46. Adeola, A. O., Nomngongo, P. N. (2022). Advanced polymeric nanocomposites for water treatment applications: A holistic perspective. *Polym.*, Vol. 14, 2462. DOI: 10.3390/polym14122462
47. Giwa, A., et al. (2019). Polymeric materials for clean water. *Springer*, pp. 167-190. DOI: 10.1007/978-3-030-00743-0
48. Khodakarami, M., Bagheri, M. (2021). Recent advances in synthesis and application of polymer nanocomposites for water and wastewater treatment. *J. Clean. Prod.*, Vol. 296, 126404. DOI: 10.1016/j.jclepro.2021.126404
49. Beyene, H. D., Ambaye, T. G. (2019). Application of sustainable nanocomposites for water purification process. *Sustainable Polymer Composites and Nanocomposites*, pp. 387-412. DOI: 10.1007/978-3-030-05399-4_14

50. Ardhiyanto, N. K., et al. (2019). Multi responses optimization of plastic injection molding for biodegradable polymers using Taguchi method and TOPSIS. *AIP Conf. Proceed.*, Vol. 2097(1), 030064. DOI: 10.1063/1.5098239
51. Alaaeddin, M. H., et al. (2019). Polymer matrix materials selection for short sugar palm composites using integrated multi criteria evaluation method. *Compos. B: Eng.*, Vol. 176, 107342. DOI: 10.1016/j.compositesb.2019.107342
52. Narayanan, N. S., et al. (2019). Evaluation and optimization of surface roughness and metal removal rate through RSM, GRA, and TOPSIS techniques in turning PTFE polymers. *Adv. Manufact. Tech.*, Vol. 2019, pp. 595-605. DOI: 10.1007/978-981-13-6374-0_65
53. Chohan, J. S., et al. (2020). Taguchi S/N and TOPSIS based optimization of fused deposition modelling and vapor finishing process for manufacturing of ABS plastic parts. *Materials*, Vol. 13(22), 5176. DOI: 10.3390/ma13225176
54. Yadav, R., Lee, H.-H. (2022). Fabrication, characterization, and selection using FAHP-TOPSIS technique of zirconia, titanium oxide, and marble dust powder filled dental restorative composite materials. *Polym. Adv. Tech.*, Vol. 33(1), pp. 3286-3295. DOI: 10.1002/pat.5780
55. Zhang, K., Zhan, J., Yao, Y. (2019). TOPSIS method based on a fuzzy covering approximation space: An application to biological nanomaterials selection. *Inform. Sci.*, Vol. 502, pp. 297-309. DOI: 10.1016/j.ins.2019.06.043
56. Loganathan, T. M., et al. (2021). Effect pf *Cyrtostachys renda* fiber loading on the mechanical, morphology, and flammability properties of multi-walled carbon nanotubes/phenolic bio-composites. *Nanomat.*, Vol. 11(11), 3049. DOI: 10.3390/nano11113049
57. Shunmugesh, K., Panneerselvam, K. (2017). Optimization of machine process parameters in drilling of CFRP using multi-objective Taguchi technique, TOPSIS and RSA techniques. *Polym. Polym. Compos.*, Vol. 25(3), pp. 185-192.
58. Prahburam, T., et al. (2022). Optimization of operation parameters in machining of functionally graded metal matrix composite using TOPSIS. *Materials Today: Proceedings*, Vol. 62, pp. 429-433. DOI: 10.1016/j.matpr.2022.03.562
59. Sharma, A. K. (2021). EDM process parameters impact on MRR and TWR for titanium alloy [Ti6al4v] and their optimization using Taguchi and TOPSIS method - An experiential analysis. *IOP Conf. Ser.: Mater. Sci. Eng.*, Vol. 1116, 012030. DOI: 10.1088/1757-899X/1116/1/012030
60. Patel, P. B., et al. (2015). Evaluation of FDM process parameter for PLA material by using MOORA-TOPSIS method. *International Journal of Mechanical and Industrial Technology*, Vol. 1(3), pp. 84-93.