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Combining of PCA and ANP methods to identify and prioritize water pollutants and employing mathematical model to reduce environmental risks emphasis in petroleum and petrochemical industries

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Water contamination is one of the important problems and challenges in the world and Iran. It is one of the main causes of death and mortality in the world. Surface and ground waters both are exposed to different contaminants. Considering the nature, source of entrance, being man-made or naturally occurring, various classifications have been considered for contaminants. The main organic contaminants of water are: agricultural, chemical, oil, and food contaminants. Each of these four groups has sub-criteria. In this research, investigation, identification, and accurate ranking of water contaminants in oil and petrochemical industries have been dealt with using factor analysis and analytical hierarchy process methods. The results of factor analysis method suggest that fact that the contaminants nitrate, sodium, and TDH have claimed the highest score from the experts of environment regarding water contamination. Further, the results of ANP showed that agricultural and oil contaminants with the weights of 0.321 and 0.152 stand in the first and fourth ranks, respectively. In this research, following investigation and ranking of water contaminants in oil and petrochemical industries, using factor analysis and ANP methods, a mathematical model was presented and then solved using goal programming with the aim of predicting and extracting the main contaminants and their levels in oil and petrochemical industry and decreasing the environmental contaminants. The researchers hopes that by presenting it to relevant organizations, an effective step is taken to prevent environmental destruction by the contaminants of this industry.

Keywords: water contaminants, analytical network process, principal components analysis, goal programming, petroleum and petrochemical industry, mathematical modeling

INTRODUCTION

Today, with the centrality of demand market, the significance of supply chain has developed so much that it has changed into one of the vital tools in commercial competitions. On the other hand, environmentalism has become one of the important commercial social issues. Based on the significance of these two issues, green chain concept was developed and grabbed by pioneering companies in global competition [1]. Today, the managers of leading companies are trying to benefit from their improved environmental performance throughout the entire supply chain as a strategic weapon for gaining competitive advantage through developing utility and satisfaction environmentally. Further, the environment that has surrounded human beings and allowed him to live is being seriously threatened by the human themselves. Now we live in an era when the issue of environmental contamination has attracted the attention of experts more than ever due to the rapid growth of population, industry, and limitations of natural resources. It has also been grasped by the public as a tangible each. In today's societies, the significance of environmental protection seems to be something essential and evident. Undoubtedly, taking any measures or implementing any programs requires sufficient knowledge of the environment and its contaminants. The environmental crises caused by contaminations are currently threatening many countries seriously. Therefore, the country can control these environmental crises through serious and logical protection from the environment and scientific plans. In this regard, recognition of water contamination and industries that develop contaminations has facilitated the ways to coping with these contaminations.

The main cause of water contamination is wastewater. Urban and household wastewaters i.e. the wastewaters resulting from household washing which are full of microbe, are poured into rivers and wells. Furthermore, industrial wastewaters which contained chemical and toxic compounds as well as agricultural wastewaters in which pesticides and chemical fertilizers are seen, cause contamination. The main cause of water contamination in the

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for agriculture with the aim of increasing productivity in terms of econometrics in Italy. In this research which has been conducted in Basilikata region in Italy, to filter the refuse resulting from chemical wastes, mean weights method and verbal quantifier were used. Based on this, a suitable map for decreasing the products of a country which was far from chemical and especially water wastes was determined across the region of interest. According to geological and agricultural scales used in this research, the researchers found that out of the entire studied region, on the 25 hectares out of the 163 hectares available are cultivable. Further, the results of this research confirmed the fact that if entrance of chemical and especially water wastes into subsurface waters of agricultural regions is not prevented, these regions will go on the verge of devastation. In another research, Lam&Dai [7] evaluated the risks in production of fresh agricultural products in despite of the greenness of its leaves along its supply chain in Europe. In this research, based on the investigations on a wide range of environmental contaminants and especially water contaminants, they found that the threatening risks are not merely a general health risk by viruses in chain foods and by only identifying and evaluating the viruses in products in retailing, it cannot be tackled with. Accordingly, presentation of a solution in this regard is very crucial. In this research, using a conceptual model and investigating the indicators affecting the quality of agricultural products including the level of water contaminants such as phenol, ammonium, and nitrate present in several foods cultivated close to chemical industry centers in several points of the EU member countries, the negative effect of these contaminants on the quality of products has been abundantly found. The results of the research on several special agricultural products such as lettuce and soft fruits such as strawberry in contaminated regions in comparison with clean regions showed that the quality of these crops had a reduction in the quality by 97.5% and this reduction of quality is due to discharging the contaminants of the chemical industries present in the region towards agricultural farms.

Wang & Samuel [8] estimated the environmental technical efficiency and its regulatory costs. In this study, quality non-radial distance function theory has been used to develop a general method for modeling the characteristics of sustainable production for electronic information industry in China. In this model, for the output variables, gross production (G) has been chosen. Labor force (L) and capital (K) are two basic inputs of the production process. Energy consumption of fossil fuels in total, equivalent to standard coal, has been chosen as the energy input. Further, emission of carbon dioxide gas is another input variable. Eventually, Grenger causality test indicates that limitation of environmental regulations is the cause of technical innovations and using Porter hypothesis, it can be found that a higher technical efficiency will result in stricter environmental regulations. Eventually, it shows that the shadow price of emission of carbon dioxide gas has had a descending trend between 1980 and 2012 due to the continuation of the increase in the extent of production of greenhouse gases and the wickedness of carbon emission regulations. Similarly, Liu et al. [9] dealt with mathematical modeling of production and biological treatment plant of energy products. They believe that mathematical models have been widely used for simulation of all aspects of biological energy production systems including the kinetics of the growth of energy products, conversion processes, production economy, logistics supply, and environmental effects. However, there is a limited commercial experience in the production and energy of product process at large scale across the world. Therefore, they present a model that is able to give a powerful tool to design biological energy and evaluate the technical, economic feasibility and environmental effects of it. The product growth model can be used for estimation of the efficiency of energy products in a region under different growth conditions and geographical information system (GIS). It has also the potential to maximize the energy production out of energy products by identifying the ground suitable for their growth. The presented model is a combination of process model and reaction kinetics and advanced computational tools for designing and optimizing different biomass conversion processes. In this research, lifecycle assessment model (LCA) has been used for comparing the environmental effects of different technologies for production of biomass and conversion. The variables used in this model include the potential rate of solar radiation ray operation coefficient, the artificial value of active radiation, leaf surface index, crown coefficient, and withdrawal index. Continuing the research in 2015, Memari et al. [10] developed a multi-objective mathematical model in a green supply-chain network consisting of producers, distribution centers, and sellers in a case study for car manufacturing. The main objectives considered in the research include minimizing the costs of production, distribution, maintenance, and the cost of shortage in authorized dealers as well as minimizing the environmental effects of the logistics network. Eventually, in addition to minimizing the costs and environmental effects especially emission of greenhouse gases, the presented model can improve the level of economic green production through on time procurement. In this research, multi-objective genetic algorithm has been used and finally the performance of the model was tested using MOGA. In another study Mulbry et al. [11] conducted a research to examine the gas contaminants emitted along supply-chain process. In their model, to combat uncertainty, problematic parameters including demand, capacity, and cost were considered as fuzzy parameters. The problem was solved using GAMS software and then sensitivity analysis was performed on its parameters. They believe that this is the first investigation that has dealt with presentation of a programming linear fuzzy multi-objective model for optimization of the natural gas supply chain through an approach to decreasing greenhouse gases. Further, in another study in this field, Rajala et al. [12] studied the relationship between managerial agencies, organizational identity, and commercial ecosystems considering green business model. They discussed the manner of changes in managerial thought of the company to develop the abilities required for change. Eventually, this paper has deals with presenting a new concept of the green business model of a company through developing a relationship between the knowledge body in strategic change. Also, Razmi et al. [13] introduces a bi-objective supply chain network design, which uses fuzzy programming to obtain the capability of resisting uncertain conditions. The design considers production, recovery, and distribution centers. The advantage of using this model includes the optimal facilities, locating them and assigning the optimal facilities to them. It also chooses the type and the number of technologies, which must be bought.

In 2014, Rohani et al. [14] evaluated the effect of sustainable supply-chain in reducing environmental contaminants. In this study, they dealt with that analysis of the supply-chain of chalk layer using mixed lifecycle method in manufacturing industry of one of the major distributors and contractors of construction materials in Europe based in England. The results of this research indicated that to decrease the environmental contaminants in distribution process, crossover warehouses can be used along the supply-chain.

MATERIALS AND METHODS

In this research, the methodology is of applied type, in terms of objective, while in terms of type, it is an assessment method based on questionnaire analysis in the real world; it can be put forward as a case study. Determining the input and output indices, obtaining and extracting the variables in this type of research itself are important parts of implementation of this research. The following steps were taken:

- Determining the criteria through the research background and PCA method -
- Development of questionnaire
- Examining the reliability of the questionnaire
- Data collection
- Determining the validity of the items of the collective questionnaires
- Giving weights to the variables
- Analysis and ranking using ANP method
- Design mathematical modeling

Principal component analysis (PCA)

Principal component analysis is one of the classic multivariate methods and perhaps their oldest and most famous method. This method was first developed to analyze the structure of variance-covariance matrices and correlation coefficient. As with many multivariate methods, prior to invention of computers, this method was not widely used due to complexity of calculations. Thereafter, in terms of theory and application, it was widely developed and employed. This type of analysis can be focused on from several perspectives.

- Conversion of dependent variables to uncorrelated variables
- Finding linear combinations with large or small relative variability
- Reduction of the volume of data
- Data interpretation

This type of analysis is not usually considered a final analysis, rather it is mainly used as an intermediate tool for further studies and investigations. The mathematical aspects used in this research involved eigenvalues and the Eigen vectors of symmetrical always positive matrices. Reduction of the volume of data is the main objective of this analysis, where these data consist of a large number of variables with internal correlations, such that the maximum available information possible in the data is kept. This takes place through converting the data (variables) to new variables which are called principal component and are uncorrelated. They are prioritized in an order that a small number of them often bring the changes in the initial variables with them. In the analysis of principal component, although seemingly the main focus is on the variance of variables, considering the relationships between the variances and covariance's, this method also takes covariances or correlation coefficients into consideration implicitly.

Analytical network process (ANP)

Saffar et al. [15] presented a method for multi-criteria decision-making. This method is called analytical network process (ANP) which has the aim of developing a model through which complex multi-criteria decision-making problems are analyzed into smaller components and through logical initialization they are converted to simpler components and finally combination of these values help in final decision-making. ANP method is the developed form of AHP method which is able to model the correlations and feedbacks between the elements affecting a decision-making and can take all internal effects of the effective components in decision-making into consideration and introduce them into the calculations. Therefore, with the help of this characteristic, this technique is superior then the previous relevant models. Indeed, it can be stated that AHP is a special form of ANP method. ANP method has two main parts, which combines these two parts in a process. The first part involves groups consisting of controlling criteria and sub-criteria as well as the group which takes the options of the volunteer. The second part is a network of vectors and arcs which represent the dependencies and correlations and the feedbacks present in the decision-making system. Eventually, this method is based on conducting paired comparisons which is similar to the paired comparisons performed in AHP method. Analytical network process can be called the most complete multi-criteria decision-making method which has been presented so far. However, the single important problem in this model is performing paired comparisons. This problem which also exists in AHP method is considered problematic as a decision-maker is not always facing accurate states of commenting and in many decision-makings of the real world, the decision-makers cannot make decisions about paired comparisons with certainty. The modeling process involves the following stages [16]:

- The first step, basing the model and structure of the problem
- The second step, paired comparisons matrix and estimation of the relative weight
- The third step, development of the preliminary super matrix
- The fourth step, development of weighted super matrix
- The fifth step, calculation of the general weighted vector
- The sixth step, calculation of the final weight of the criteria

Introduction of the influential criteria and sub-criteria in the evaluation process

In this research, by presenting a framework, to identify and prioritize the extent of greenness of production industries and presentation of a solution for enhancing the greenness of supply chain. According to the background and interview with experts, the criteria effective in the evaluation process have been developed as the steps presented in the research according to Fig. 1. In this model, the aim is identification and prioritization of industrial contaminants in water (wastewater) which lies at level I. the production industries which include food industries, chemical industries, agriculture industries, and oil industries in two petrochemical and refineries of the oil in Tehran have been shown at Level II, which are in the form of nitrate (NO_3), nitride (N_3^-), and ammonium (NH_3) present in food industries, phosphate (PO_4), sulfate (SO_4), and chloride (Cl^-) present in chemical industries, phenol (C_6H_5OH), sulfide (H_2S), oil, mercury (Hg), and cadmium (Cd) present in oil industries, and nitrate (NO_3), ammonium (NH_3), phosphate (PO_4), and chloride (Cl^-) present in agricultural industries, which are considered as sub-criteria. BOD, COD, TDS, and TSS which are known as comparative evaluation indices of contaminants across all production industries are considered as the sub-criteria at Level III. Finally, these contaminants are prioritized in industry in the order of contamination in the environment. The list of the contaminants includes the following [17,18]:

Introduction of the criteria that detect the contaminants

Biochemical oxygen demand (BOD): oxygen consumption rate inside water by organisms. If BOD is low, water is clean and lacks any organism or the organisms inside water are dead and have no need to consume oxygen. BOD is the amount of oxygen required for biological stability in water. The size of facilities of biological treatment especially the wastewater aeration rate in aeration basins can be calculated by BOD level. If water BOD is 1 ppm, then the water is almost pure. Water with a BOD up to 5 ppm is considered to be relatively pure, but when it exceeds 5 ppm, purity of water is questioned. However if its value goes beyond 20 ppm, the public health is jeopardized. BOD experiments provide a realistic estimation of the quality of oxygen that has been introduced into the water [19].

Chemical oxygen demand: it is the amount of oxygen that is required so that the organic compounds present in the sample are chemically stabilized. The utilized oxidizer is usually potassium dichromate in the presence of sulfuric acid. Wastewater contamination caused by the external compounds that enter water as suspended or soluble form, cause its contamination and production of wastewater. Evidently, the higher the level of these compounds in wastewater, the greater its contamination load. Therefore, measurement of the amount of external compounds of wastewater is the major key in determining the extent of contamination of wastewater [18].

Total dissolved solids or concentration of minerals: it is the amount of organic compounds or mixed inside a liquid, where these compounds can exist in water as molecular or ionized form or very tiny grains at micron level as a suspended form. The primary resources (major applications) for TDS in receiving waters, the waters resulting from agriculture and residential areas, soil contamination washing and the contaminated water resources discharged from industrial units and wastewaters. The most important aspect of TDS, taking water quality into consideration, is its effect on the taste of water. Clarity and transparency of water with a TDS lower than 600 mg/l is generally considered a good state. Drinking water with a degree above 1200 mg/l is considered an unfavorable state by the majority of consumers. The difference between TDS and TSS lies in the fact that in TSS the particles cannot pass through a filter with a 2-micron scale and remain suspended in the solution for an unknown time [8].

Classification of water contaminants

The processes for selecting the selection criteria of the extent of contamination of industries are based on the two following areas:

Investigation of the criteria used by previous researchers

- Study of the contamination indices and important contaminating industries according to managers and experts of environment

Based on the mentioned process, a set of the most important selection indices of industries and contaminants were considered as the main measurement criteria.

1. **The criterion of contamination of food industries**: Based on the extent of significance and development of these contaminants in groundwater's, the criterion of food industries consists of three sub-criteria of "nitrate", "phosphorus", and "protein" [15].
2. **The criterion of contamination of chemical industries**: The four following criteria are considered the most important sub-criteria of the characteristics of this industry in laboratory trusted by the environment, which have been selected at this stage: lead, mercury, copper, alkalinity of suspended solids and heavy metals [16].
3. **The criterion of contamination of oil industries**: the following sub-criteria are among the most important ones of this industry in measuring the extent of contamination: phenol, hydrogen sulfide, oil, ammonium, and TPH [17].
4. **The criterion of contamination of agricultural industries:** furthermore, the following criteria have been considered as the sub-criteria associated with agricultural industries: nitrate, chemical fertilizers, sediments, and TOG [18].

Fig. 1. Represents the major contaminants by individual types.

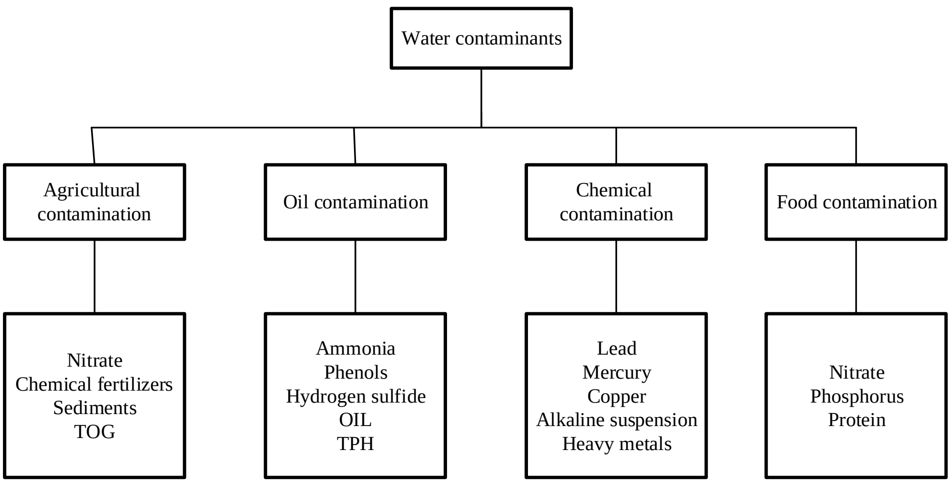

Fig. 1. Classification of the contaminants.

RESULTS

Next comes explanation of the results of the open-ended questionnaire and analytical network process method. Last part of this section we introduce the mathematical model for minimizing the contaminants then we solve the mathematical models based on read world dataset of oil and petrochemical industries.

Statistical analysis

According to the previous studies, 20 water contaminant indices were extracted and then distributed among 145 experts, so that based on their previous background, a score between 1 (the least significant) and 10 (the most significant) would be given. Accordingly, for ranking the contaminants, statistical methods and especially factor analysis and PCA were used. Then, we deal with explanation of the results of the open-ended questionnaire. Tables 1-3 present the preliminary factor analysis of the indices for estimating the contributing performance of each of the contaminants on the problem's objective.

Table 1. The ratio of the variance of each of the contaminants

Communalities		
	Initial	Extraction
Nitrate	1.000	.783
phosphor	1.000	.671
PH	1.000	.667
OIL	1.000	.667
TDS	1.000	.712
heavy metals	1.000	.579
TSS	1.000	.559
Ammonia	1.000	.599
Phenols	1.000	.532
Protein	1.000	.491
Chemical fertilizers	1.000	.627
COD	1.000	.591
Sediments	1.000	.712
Hydrogen sulfide	1.000	.684
Lead	1.000	.708
Mercury	1.000	.725
Copper	1.000	.726
DO	1.000	.572
BOD	1.000	.472
Extraction Method: Principal Component Analysis.		

Table 1 provides the ratio of the variance of the scores taken by each contaminant by the experts. As can be observed in the table, the contaminants nitrate, sodium, and TDS have claimed the highest score by the experts of environment regarding water contamination.

Table 2 presents the frequency distribution of the sum of the variance of contaminants. In this table, the results were investigated based on PCA method. In the above table, Initial eigenvalues column represents the variance associated with the complete set of contaminants from the initial results. Furthermore, the column of extraction sums of squared loadings demonstrate the variance of the most important contaminants among all the contaminants.

Table 3 indicates the correlation matrix between all of the contaminants with nine selected contaminants which had the greatest contamination variance as commented by experts according to Table 2. Based on the results of this table, all of these contaminants have a low correlation with each other

Table 2. The sum of distributional variance of the contaminants

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.759	9.257	9.257	1.759	9.257	9.257
2	1.621	8.533	17.789	1.621	8.533	17.789
3	1.529	8.049	25.839	1.529	8.049	25.839
4	1.392	7.325	33.163	1.392	7.325	33.163
5	1.374	7.234	40.397	1.374	7.234	40.397
6	1.178	6.199	46.596	1.178	6.199	46.596
7	1.142	6.013	52.609	1.142	6.013	52.609
8	1.078	5.672	58.281	1.078	5.672	58.281
9	1.000	5.266	63.546	1.000	5.266	63.546
10	.970	5.103	68.649			
11	.898	4.728	73.377			
12	.857	4.509	77.886			
13	.811	4.267	82.153			
14	.739	3.890	86.043			
15	.667	3.511	89.554			
16	.610	3.209	92.763			
17	.523	2.750	95.513			
18	.469	2.471	97.984			
19	.383	2.016	100.000			

Extraction Method: Principal Component Analysis.

Table 3. The correlation matrix between each of the contaminants

Component Matrix(a)

	Component								
	1	2	3	4	5	6	7	8	9
TSS	-.583	.098	.315	.224	.149	.011	.181	.057	.046
TDS	.572	-.169	.230	.350	.044	.000	-.056	-.416	-.046
Lead	.534	-.087	.248	-.086	-.303	-.040	.035	.270	-.423
Chemical fertilizers	.070	.566	-.202	.171	.043	-.031	.003	-.432	-.204
heavy metals	.213	-.503	.260	-.230	.278	-.149	.183	-.077	.149
Ammonia	.365	.488	.227	-.112	.088	.253	-.048	.300	-.009
Sediments	.126	.138	-.674	.185	.150	.217	.243	.029	.244
Mercury	-.215	.205	.472	.187	-.392	.307	.042	-.343	.103
Phenols	.104	.327	.275	.379	.275	.299	.041	.147	-.077
BOD	.362	.040	-.095	.375	.246	.001	-.109	.085	.331
Copper	-.215	-.314	.110	-.170	.525	.319	-.249	-.061	-.312
DO	.158	-.202	.291	.404	.432	-.156	-.156	.065	.137
COD	-.124	-.350	-.055	.358	-.383	-.206	-.257	-.123	.227
Nitrate	.131	.112	.283	.044	-.030	-.402	.712	-.039	-.012
phosphor	.198	.348	.174	-.172	-.178	-.300	-.561	.005	.120
OIL	-.179	-.235	.170	.344	-.382	.321	.022	.422	.070
Protein	.033	.053	-.250	.312	-.019	-.356	-.021	.414	-.170
Hydrogen sulfide	.414	-.098	.016	-.360	-.156	.363	.124	.022	.447
PH	-.269	.362	.305	-.257	.217	-.276	-.078	.153	.390

Extraction Method: Principal Component Analysis.
a. 9 components extracted.

Table 4. The final ranking of the contaminants according to expert comments

Final Ranking	**Score**	contaminants
2	0.955	Nitrate
10	0.734	phosphor
4	0.808	PH
13	0.719	OIL
15	0.711	TDS
12	0.726	heavy metals
11	0.729	TSS
12	0.726	Ammonia
3	0.83	Phenols
14	0.717	Protein
16	0.707	Chemical fertilizers
7	0.764	COD
8	0.754	Sediments
14	0.717	Hydrogen sulfide
1	0.97	Lead
17	0.703	TOG
6	0.785	Mercury
5	0.788	Copper
9	0.743	DO
17	0.703	BOD

As can be observed in Table 4, Lead contaminants is considered the most important water contaminant by the experts. It is followed by nitrate with the score of 0.955, as the second rank. Furthermore, in the above table it can be deduced that several contaminants had the same score according to the experts, which include hydrogen sulfide and heavy metals, both of which had a score equal to 0.717.

Analytical network process

In order to achieve the objective of the research, paired comparisons questionnaires were designed and distributed among the experts. Considering the verbal judgment approach in this research, the statements and numbers written in Table 5 were used.

Table 5. The defined numbers.

relative comparison of the indices (verbal judgment)	Priority number
Absolute significance	9
Very strong significance	7
Strong significance	5
Weak significance	3
Equal significance	1
Intermediate values	2,4,6,8

In this section, based on the hierarchical network, the prepared paired comparisons tables and the modified method of [12], the weight of the components was obtained and they were then prioritized. The results were calculated by Super Decision software.

In this research, ANP technique was used for determining the priority of objectives. For this purpose, using ANP questionnaire, 15 (Wibisono, D., & Khan) managers and experts of the field of environment related to oil and petrochemical contaminants were requested to give their comments. Thereafter, the data written in the matrices were analyzed by Excel and Super Decision software applications. Based on them, the inconsistency rate was obtained to be 0.04. As this rate is lower than 0.1, then the obtained weights are reliable. Next, the results obtained from the analytical network process are explained in detail.

Table 6 represents the ranking of the major criteria of water contaminants. As can be observed in the table, agricultural contaminants (weight=0.321) and oil contaminants (weight=0.152) stand in the first and fourth rank, respectively. Next, in Tables 7-10, the ranking of the sub-criteria of the contaminants of each of the four major criteria is presented. The results of Table 7 indicate that the nitrate element claimed the first rank in the sub-criteria of food contaminants. Furthermore, this result confirms the first section of the research in the open-ended questionnaire, as the majority of experts had chosen this element as the second important contaminant.

The results of Table 8 indicate that the nitrate element lies in the first rank among the sub-criteria of agricultural contaminants. As was stated in the results of this sub-criteria of food contaminants, this result confirms the first section of the research in the open-ended questionnaire, as the majority of experts had chosen this element as the second contaminant.

Table 6. Ranking of the major criteria

The main criterion	Weight	Rank
agricultural contaminants	0.321	1
chemical industries	0.286	2
oil contaminants	0.152	4
food industries	0.241	3

Table 7. The ranking of this sub-criteria of food contaminants

The main criterion	Weight	Rank
Nitrate	0.455	1
Phosphorus	0.431	2
Protein	0.114	3

Table 8. Ranking of the sub-criteria of agricultural contaminants

The main criterion	weight	rank
nitrate	0.287	1
chemical fertilizers	0.255	2
sediments	0.215	3
TOG	0.243	4

Table 9. Ranking of the sub-criteria of chemical contaminants

The main criterion	Weight	Rank
alkalinity of suspended solids	0.155	4
Heavy metal	0.096	5
lead	0.382	1
mercury	0.166	3
copper	0.201	2

Table 9 represents the results of ranking the sub-criteria of chemical contaminants. As can be observed, lead with the weight of 0.382 is standing in the first rank of these sub-criteria. As had been shown in Table 4, the lead element was considered the most important contaminant by the experts in the field of oil and petrochemical industries.

Table 10. The ranking of the sub-criteria of oil contaminants

The main criterion	Weight	rank
oil	0.160	4
TPH	0.198	2
ammonium	0.301	1
hydrogen sulfide	0.188	3
phenol	0.143	5

Table 10 represents the results of ranking the sub-criteria of oil contaminants. As can be observed, ammonium with their weight of 0.301 claims the first rank in these sub-criteria. It is followed by TPH and hydrogen sulfide with respective weights of 0.198 and 0.188.

Mathematical model

In this section, Goal Programming modeling is presented considering the results of analytical network process method. Before dealing with the modeling, the variables and parameters used in the model are presented:

The sets

i	:	The index of major contaminants
I	:	The contaminant set of main indicators $I=\{1,...,m\}$
j	:	Industry index
J	:	The set of contaminants industries $J=\{1,...,n\}$
k	:	The sub-criteria of the index of main contaminants
K	:	$K=\{1,...,p\}$ the set of the sub criteria of the index of main contaminants

The decision parameters and variables

g_i	:	the minimum allowable limit of environmental contamination of the main i indices
a_i	:	the environmental contamination weight of the main i indices
l_j	:	the minimum allowable limit of environmental contamination of the main indices in the j industry
b_j	:	the environmental contamination weight of the main indices in the j industry
o_k	:	the minimum allowable limit for environmental contamination of the sub-criteria of the index of the k main contaminants
d_k	:	the environmental contamination weight of the sub-criteria of the index of k main contaminants
s_{ijk}	:	If the allowable limit of the environmental contamination of the sub-criteria of the index of k contaminants in the j industry is greater than the main i indices, it is equal to 1, otherwise it is zero.
c_{ijk}	:	The impact factor of the environmental contamination of the sub-criteria of the index of k main contaminants in the j industry of the main i indices
y_{ijk}	:	If the sub-criteria of the index of main k contaminants in the j industry is greater than the main i indices, it is equal to 1, otherwise it is zero.

Mathematical model

The mathematical formulation of the problem is described by Eq. (1).

$$\min \quad \sum_i \sum_j \sum_k c_{ijk}.y_{ijk}.s_{ijk} \tag{1}$$

Eq. (1) represents the objective function of the research problem. This relation suggests the minimum extent of environmental contamination based on their emission significance factor in the industry of interest.

Constrains

$$\sum_j y_{ijk}.s_{ijk} \le 1 \tag{2}$$

$$\sum_j y_{ijk} = g_i \tag{3}$$

$$\sum_j y_{ijk} = l_j \tag{4}$$

$$\sum_j y_{ijk} = o_k \tag{5}$$

$$\sum_i g_i \le 1500 \tag{6}$$

$$\sum_j l_j \le 250 \tag{7}$$

$$\sum_k o_k \le 1700 \tag{8}$$

$$\sum_i \sum_j \sum_k y_{ijk} a_i \le 0.35 \tag{9}$$

$$\sum_i \sum_j \sum_k y_{ijk} b_j \le 0.4 \tag{10}$$

$$\sum_i \sum_j \sum_k y_{ijk} d_k \leq 0.25 \quad (11)$$

$$S_{ijk} \in \{0.1\},\ y_{ijk} \in \{0.1\} \quad (12)$$

Constraint (2) ensures that the minimum extent of contamination in the industry is not above the allowable limit. Constraints (3)-(5) represent the minimum contamination level for the main criteria, sub-criteria, and the contaminating industry, respectively. Constraints (6) to (8) state the minimum allowable level of environmental contaminants considered in these limitations based on the results of standards of Iranian industrial research Institute and water environmental contamination national standard with the code 1053. Constraints (9) to (11) express the weight coefficient of each of the contaminants in relation with the tool told environmental contamination in each of the industries (petrochemical and oil). The level of the impact factor of each of the contaminants has been stated according to the research by [19].

Solving the mathematical model

Based on the calculations which have been shown above by the matrices in Tables 5-10, and according to the definition of the programming model in Section 4-3-3, the defined model is further solved considering the research findings and according to the contaminants.

Table 11. The allowable level of the contamination of the indices of interest in the group of agricultural contaminants

Main criterion	Unit of calculation	maximum allowable level	minimum allowable level	mean for the region	Weight
Nitrate	Mg/L	12	7	13.8	0.287
Chemical fertilizers	Number per 100 mL	Below 1000	Larger than 550	875	0.255
Sediments	Mg/L	220	143	200	0.215
TOG	Mg/L	50	32	55	0.243

Table 12. The allowable level of the contamination of the indices of interest in the group of food contaminants

Main criterion	Unit of calculation	maximum allowable level	minimum allowable level	mean for the region	Weight
Nitrate	Mg/L	14	6	13.8	0.455
Phosphor us	Number per 100 mL	0.85	0.06	0.8	0.431
Protein	Number per 100 mL	35	15	28	0.114

Table 13. The allowable level of the contamination of the indices of interest in the group of chemical Contaminants

Main criterion	Unit of calculation	maximum allowable level	minimum allowable level	mean for the region	Weight
Alkalinit y of the compounds	Mg/L	65	44	73	0.155
Other heavy metals	Number per 100 mL	Below 3	Larger than 1	4	0.096
Lead	Mg/L	Below 6	Larger than 3	8	0.382
Mercury	Mg/L	Below 12.5	Larger than 2	15.5	0.166
Copper	Mg/Platinu m	Below 5	Larger than 3	9	0.201

Table 14. The allowable level of the contamination of the indices of interest in the group of oil contaminants

Main criterion	Unit of calculation	maximum allowable level	minimum allowable level	mean for the region	Weight
Oil	Mg/L	below 7	Larger than 3	8	0.16
TPH	PH	9	5.5	7	0.198
Ammonia	Mg/L of HOCl	50	21	86	0.301
Hydrogen sulfide	Mg/L	below 400	Larger than 240	365	0.188

Phenol	Mg/L	0.08	0.001	0.11	0.143

The above model was solved by LINGO 14 software. The results can be seen in Table 15.

Table 15. The results of solving the mathematical model in the oil industry

The chemical industry	Oil industry	Variable
Value		
	Agricultural	
1	1	Nitrate
1	0	Chemical fertilizers
0	1	Sediments
1	0	TOG
	Food	
1	0	Nitrate
0	0	Phosphorus
1	0	Protein
	Chemical	
1	1	Alkalinity of the compounds
0	1	Other heavy metals
1	1	Lead
0	1	Mercury
0	0	Copper
	Oil	
0	1	Oil
0	0	TPH
1	1	Ammonium
1	0	Hydrogen sulfide
1	1	Phenol

On by oil contaminants, saturated group contaminants are meant. Based on the research findings, the contaminating branches in each of the main four groups including agriculture, food, oil, and chemicals consisting of 20 contaminating elements along with the relative significance were stated in Tables 5-10.

Based on the research findings and according to the mathematical programming model, 20 elements were identified as the environmental contaminating elements in oil and petrochemical industry as the most important elements. Considering the relative significance coefficient of each of the elements shown in W^{ANP} matrix (Table 5), the main significance is related to the agricultural contaminants, while the lowest degree of significance is associated with the contaminants of food group. Based on these points and the data in Tables 11-14, which were collected from organization of environment and credible laboratories of the province, Table 15 represents the results obtained from solving the mathematical model in both industries individually. As can be seen in Table 15, the value of 1 denotes contamination and 0 suggests no contamination. The very important point in the obtained results is the fact that based on the difference in the definition of the value of contamination level of each of the elements and environmental units of these two industries, the difference lies in the detection of whether an index is contaminating or non-contaminating, which can be clearly seen in Table 15.

CONCLUSION

Chemical contaminants which are developed with a nature different from industrial and national wastes increasingly find their way to the general water supply resources. These contaminants include detergent solutions, cyanides, heavy metals, organic and organic acids, nitrate compounds, whitening compounds, dyes, pigments, sulfides, ammonium, toxic compounds, and a wide variety of organic biocids. Chemical contaminants not only are able to damage the human health directly, they can also affect human health by indirectly concentrating in aquaculture (such as accumulation of chemicals in fishes that are used as human food). The current view about the effect of water related contaminants is two-sides. One is the acute toxic damages on human health and another is the long-term effects due to exposure to trace amounts, where this group is as important as the previous one and most of the time emerges nonspecifically and its detection is difficult. In addition, some new contaminants cannot be treated easily using traditional water treatment equipment or purification processes. In many advanced countries in which contagious transmittable diseases by water have been almost eradicated, chemical contaminants are more cared for. As it was indicated in Table 4, lead contaminant is the most important water contaminant according to experts. This element is followed by nitrate with the score of 0.955. Furthermore, in this table it can be deduced that several contaminants had the same score according to the experts, which include hydrogen sulfide and heavy metals, both of which had a score of 0.717.

In future research, other probabilistic modeling approaches can be used or with a combinational approach, fuzzy systems and artificial intelligence can also be employed, and the results can then be compared with each other. Furthermore, it is possible to benefit from robust approach to allocate and correspond with uncertainty.

The following is a list of other offers:

– Integration of the strategic decisions with tactical/operational decisions. For example, in the issue of management of industrial wastewaters and emission of greenhouse gases, the presented suggested models can result in saving on the up to a certain level. A greater level of saving can be accompanied by strategic and large-scale decisions such as construction of treatment systems or to ideological development of construction processes. On the other hand, other strategic decisions such as construction of new production companies and suppliers can also be very interesting.

– further, as the waste water from chemical processes of companies is considerable and environmental contamination is also an issue for the organization of environment, if these contaminations exceed a certain environmental determined level, it will lead to considerable fines, thus for future research, the factor of air pollution can also be added to the problems and the results can be investigated.

– Development of other heuristic and metaheuristic methods for multi-objective optimization problems under uncertainty conditions with large-scale

– modeling in a decentralized form and comparing its weak and strong points, in relation with a centralized approach (in the proposed models, all tactical and operational decisions have been modeled by the main company and by considering the profit and loss of the entire chain in a centralized form, the decentralized approach can be taken in a way that in the supply chain, each company is program individually such that it is able to both optimize its program and in a multiparty game of the entire chain, moves towards the total optimum).

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