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# Impact of the heated water discharge on the water quality in a shallow lowland dam reservoir

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**Abstract:** The purpose of the work was to determine the relationship between the of the water quality parameters in an artificial reservoir used as cooling ponds. Factor analysis were applied to analyze eighteen physico-chemical parameters such as air and water temperature, dissolved oxygen concentration, visibility of the Secchi disk, concentrations of total nitrogen, ammonium, nitrate, nitrite, total phosphorus, phosphate, concentrations of calcium, magnesium, chlorides, sulfates and total dissolved salts, pH, chemical oxygen demand and electric conductivity from 2002-2019 to investigated cooling water discharge. Exploratory factor analysis allowed identified four factors were obtained from 54.1% (in discharge zone) to 56.7% (in dam zone). In discharge and pelagic zones confirmatory factor analysis showed that four latent variables: salinity, temperature, nitrogen and phosphorus provide good fit, but in the dam zone the better fit was obtained for the latent variables salinity, temperature, nutrient and eutrophic. Correlations between latent variables temperature, nitrogen, phosphorus or nutrient and eutrophic show a significant effect of temperature on the transformation of nitrogen and phosphorus compounds.

## Introduction

Production of electric energy in thermal power plants is related to the availability of fuels (coal, petroleum, natural gas) and cooling agents (water, air). In Poland, coal is the basic energy resource. In 2018, 42.6 $10^6$ Mg of hard coal and 58.1 $10^6$ Mg of lignite were utilized in power plants, combined heat and power plants and thermal power stations. (Statistical Yearbook of Republic of Poland 2019).

The government forecasts state that there will be a decrease in the electric energy production in the power plants based on hard coal and lignite in Poland. However, coal will remain the main resource for the electric energy production until 2040 (Table 1). The increasing percentage of natural gas and nuclear energy will result in the increase of the thermal power plant share in the energy balance.

Functioning of the cooling system for the power plant devices is a significant factor that affects the electric power production efficiency. For that reason, water management is an important element in the thermal power plant exploitation and maintenance.

The thermal power plants, both nuclear and conventional ones, use steam turbines with the heat efficiency of approx. 34–39%. Over 60% of the thermal energy must be dispersed as the waste heat. Various cooling systems are used, which depends on local conditions.

Open once-through systems are used at places where large water amounts are available. In such systems, the collected cooling water is discharged into the same water reservoir (river, lake, cooling pond) after it leaves the condenser. Under typical conditions, the discharge of heated water causes the temperature rise by 8–12°C. It requires an intake of approx. 125 $m^3/s^{-1}$ of water for a power plant with installed capacity of 3,000 MWe (Dyer at al. 2017), but the non-returnable water consumption is low.

When the water access is limited, the closed-loop or open recirculation systems (cooling towers) are used, in which the water consumption results from the necessity to compensate for the loss in the cooling system. (Reference Document on the application of Best Available Techniques to Industrial Cooling Systems December 2001) (Table 2).

The heated water management is particularly important in Poland as the amount of the cooling water discharged into the surface water was $6.008 \cdot 10^9$ $m^3$ in 2018, which constituted 73.3% of all the wastewater discharged into water and soil. (Statistical Yearbook of Republic of Poland 2018)

The water delivered to the cooling systems requires appropriate treatment in order to prevent device corrosion, lime scale deposit and microbial growth (microbiological corrosion). The water treatment technology depends on the local conditions and cooling system type (closed-loop or open). In the open systems (contrary to the closed-loop ones), relatively simple water treatment methods are applied.

The waste heat, chemicals and waste are discharged into the surface water, which produces a negative effect for the environment. The heated water discharge poses an environmental threat for the surface water and also causes the water temperature rise and decrease of the dissolved oxygen concentration (Bloemkolk and van der Schaff 1996), which results in:

- the disruption to the natural functioning of the surface water ecosystem due to the aspiration and destruction of living organisms (microorganism, fish, etc.) in pipes, ducts and heat exchange systems for cooling water;
- the discharge of chemicals used to prevent biological and physical pollution of the cooling system (e.g. biocidal agents, dispersing and anti-corrosion agents and products of their degradation);
- the contamination of the surface water with the process chemicals penetrating the cooling water (oils, aromatic compounds, organochlorides). (Kowalski and Mazierski 2008).

In summer months, it is possible to exceed the environmental quality standards (EQS) for water. Consequently, the primary production processes may increase and changes in the species composition of water organisms (particularly unicellular algae) may occur, which largely reduces water transparency (Johst and Rothsteinn 2014). The changes can be classified as the direct or indirect ones. The direct effects consist in the changes in the species composition and physiological processes (caused, among others, by the parasite invasion) (Rajagopal et al 2012). The indirect effects are related to the changes in the hydrological conditions resulting from the collected and discharged water amounts.

The impact of the heated water discharges on the water quality under moderate climate conditions was researched i.a. in Konin Lakes. It was found out that the decrease in the dissolved oxygen concentration occurred together with the temperature rise. The temperature rise was also related to the increased load with nutrients and growth of the zooplankton

**Table 1.** Forecast for net achievable power sources for energy generation until 2040 according to the technology [MW]. (Conclusions from the forecast analysis for the energy production sector – annex no. 2 to Poland's energy policy until 2040 (PEP 2040 – ver 2.1). Ministry of Energy Warsaw 2019) (in Polish)

| | **2020** | **2025** | **2030** | **2035** | **2040** |
|---|---|---|---|---|---|
| lignite power plants – old | 7.481 | 6.992 | 6.992 | 4.098 | 2.939 |
| lignite power plants – new | 451 | 451 | 451 | 451 | 451 |
| hard coal power plants – old | 12.126 | 10.867 | 7.983 | 3.539 | 3.184 |
| hard coal power plants – new | 3.520 | 4.450 | 4.450 | 4.450 | 4.450 |
| hard coal-fired CHP plants | 4.713 | 4.383 | 3.544 | 3.123 | 2.714 |
| industrial CHP plans | 1.925 | 1.740 | 1.710 | 1.898 | 1.826 |
| natural gas power plants | – | 1.900 | 1.900 | 3.039 | 3.260 |
| natural gas CHP plants | 2.688 | 3.807 | 4.371 | 4.100 | 5.261 |
| nuclear power plants | 0 | 0 | 0 | 2.600 | 3.900 |
| pumped storage power plants | 1.415 | 1.415 | 1.415 | 1.415 | 1.415 |
| hydropower plants | 995 | 1.110 | 1.150 | 1.190 | 1.230 |
| biomass power and CHP plants | 658 | 1.143 | 1.531 | 1.536 | 1.272 |
| biogas CHP plants | 305 | 517 | 741 | 945 | 1.094 |
| onshore wind farms | 9.497 | 9.574 | 9.601 | 9.679 | 9.761 |
| offshore wind farms | 0 | 725 | 3.815 | 5.650 | 7.985 |
| solar farms | 2.285 | 4.935 | 7.270 | 11.670 | 16.062 |
| gas turbines / reserve / import | 0 | 0 | 0 | 350 | 350 |
| demand side response (DSR/storage/ interconnectors | 550 | 1.160 | 2.150 | 3.660 | 4.950 |
| together | 48.656 | 55.167 | 59.073 | 63.391 | 72.103 |

DSR – demand side response

**Table 2.** Approximate cooling water intake and consumption without taking into account ambient temperature or plant efficiency (rounded and adapted from EPRI 2002) (Reference Document on the application of Best Available Techniques to Industrial Cooling Systems. 2001)

| Power plant | Cooling system | Water intake [$m^3$/MWh] | Water consumption [$m^3$/MWh] |
|---|---|---|---|
| Fossil fuel /biomass/ waste | Once-through | 76.0–190.0 | 1.0 |
| | Closed – loop | 2.0–2.3 | 2.0 |
| Nuclear steam | Once-through | 95.0–230.0 | 1.5 |
| | Closed – loop | 3.0–4.0 | 3.0 |

and primary production. (Koczorowska 2001, Choiński and Ptak 2013).

The aim of the current paper was to describe the effects of heated water discharge on the relationship between water qualities parameters

## Principal component analysis / Exploratory factor analysis

Principal component analysis (PCA) is a statistical method used to reduce the number of dimensions for the multivariate problems (Johnson and Wichern 1992) and to find a set of principal components that are an orthogonal linear combination of the observable variables. As the subsequent principal components explain a decreasing variance range, it is possible to reduce their number. The limited number of the principal components provides information on the most significant parameters, which helps to explain the majority of the variance for the original multidimensional data (Jolliffe 1986).

The principal components can be expressed with the dependence:

$$z_{i,j} = a_{i,1}x_{1,j} + a_{i,2}x_{2,j} + a_{i,3}x_{3,j} + \ldots + a_{i,m}x_{m,j}$$

where: $z$ is the result variable called the component score; $a$ is the factor loading; $x$ is the measured value of variable; $i$ is the component number; $j$ is the sample number; $m$ is the total number of variables (Helena et al. 2000, Kannel et al. 2007, Rodrigues et al. 2010)

The main objective of the Exploratory Factor Analysis (EFA) is to identify the non-observable variables and to construct a model of the examined phenomenon. It is based on the assumption that the observable variables can be presented with the linear function of the non-observable variables (factors) common for the entire set of the input variables and one non--observable factor specific for that variable. Within the proper factor analysis, a few methods for the factor distinguishing are used. The most often used ones are the Maximum Likelihood (ML) method and Principal Axis Factoring (PAF) procedure. Additionally, the PCA is often used at the initial calculation stage. To facilitate the result interpretation, the coordinate system rotation is used in such a way that each observable variable could be strongly correlated only with one factor and each factor could have a few close loadings of 0 and a few high or close loadings of 1 or -1. Such an approach eliminates the ambiguity in the obtained model interpretation. If it is valid to assume that the factors are orthogonal (i.e. not mutually correlated), the Varimax, Quartimax or Equamax rotations are used. When the factors are correlated, the Oblimin or Promax rotations are applied.

The following dependence is used in the EFA:

$$z_{i,j} = a_{f1}x_{1i} + a_{f2}x_{2i} + a_{f3}x_{3i} + \ldots + a_{fm}x_{mi} + e_{fi}$$

where $z$ is the measured value of the variable; $a$ is the factor loading; $f$ is the factor score; $e$ is the residual term accounting for errors or other sources of variation; $i$ is the number of samples; $j$ is the number of variables; $m$ is the total number of factors (Gao et al. 2011, Kim et al. 2017).

## Confirmatory factor analysis

Confirmatory factor analysis (CFA) is an extension of EFA and allows you to verify the fit of the obtained model and compare competing models. (Dragan and Topolŝek 2014, Kowalska-Musiał and Ziółkowska 2013) Using the knowledge of the studied phenomenon, a specific structure and number of factors are assumed in accordance with the previously adopted theoretical assumptions However, it should be noted that in confirmatory factor analysis each indicator is loaded by only one factor, with all other loadings set to zero. This strict requirement of zero cross-loadings is a signify cant limitation of the CFA.

The model verification consists in checking the consistency of the co-variance matrix based on the model with the co-variance matrix of the observable variables. The $\chi^2$ statistics is used as the model fit index. Due to many limitations of the $\chi^2$ test, a number of indices originating from the $\chi^2$ function were introduced. They are called the absolute fit indices and include, among others, the Jöreskog and Sörbom's model of the goodness of fit index (GFI) and its correction, i.e. the adjusted goodness of fit index (AGFI), which takes into account the numbers of variables and degrees of freedom; and the root mean square error of approximation (RMSEA). A group of comparative and parsimonious fit indices (Akaike Information Criterion, Bayesian Information Criterion) is used to compare the considered models (Wu et al. 2014).

The assessment of water quality is made on the basis of several measurement results. Striving to reduce the amount of data and simplify their interpretation contributed on the one hand to the introduction of the Water Quality Index (WQI) on the one hand, and the use of static multivariate analysis methods on the other. Literature data indicate that these methods have found wide application in both surface and groundwater research (Vega et al. 1998; Petersen et al. 2001). With the help of PCA Vega et al. (1998) with the help of PCA identified factors affecting water quality and sources of pollution. They found that mineral substances have a natural origin, while organic and biogenic pollution are associated with human activity. Similarly, Petersen et al. (2001) used the PCA method to identify factors affecting quality in the Elba River and in the estuary. They showed that water quality is affected by biological processes, and the main factors are water reaction and oxygenation as well as sewage discharge. The widespread use of multivariate analysis methods has not only allowed them to be used to assess water quality. These methods are also used to identify hidden sources of pollution and manage water resources. ; (Kumar et al. 2009, Simeonov et al. 2003; Singh et al. 2004; Boyacioglu and Boyacioglu 2017). Also in the research on the quality of groundwater multidimensional analysis methods were used (Helena et al. 2000, Liu et al. 2003, Wang at al. 2007, Hossain at al. 2013). Unusual applications include determining the quality of rainwater flowing down from roofs (Nosrati et al. 2017) the impact of deicing on water quality in the National Park (Rodrigues at al. 2010). Many authors, considering that factor analysis methods are the initial stage of analysis, used confirmatory factor analysis and modeling of structural equations. The number of publications devoted to these issues has been growing for several years. An interesting review of publications in this field was prepared by Fan et al. (2016). Much of the work is devoted to issues of pollution of water supply sources (Doria et al 2005, Viswanath et al. 2015, Masduqi et al. 2010). The results of research on phenomena occurring in the eutrophic and mesotrophic lake were published by Arsonists et al. (2006). Similar studies were conducted by Wu et al. (2014). Confirmatory factor analysis and modeling of structural equations were used to determine factors affecting the state of river purity (Boyacioglu and Boyacioglu 2018, Ryberg 2017, Mustapha and Aris 2012)

## Research object

Rybnik Lake is located in Upper Silesia, in the south of Poland. (50°08'09"N, 18°30'08"E). It was constructed in 1972 and has constituted a technological object of the power plant used to cool down the condensers of the four power blocks (capacity of 225 MW). The reservoir has an earth dam and is supplied with water of the Ruda River (SSQ flow rate: 1.23 $m^3/s$) and Nacyna River (SSQ flow rate: 0.87 $m^3/s$) (the Oder river tributaries).

Its total area (together with reservoirs on its sides) is 555 ha. The main reservoir area is 465 ha. At the normal elevation pool level (221.00 MASL), the reservoir volume is 22.099 mln $m^3$. At the flood (maximum) elevation pool level (221.30 MASL), the reservoir volume is 23.482 mln $m^3$. The total volume (together with reservoirs on its sides) is 24.0 mln $m^3$. (Rzętała 2008).

Water for cooling purposes is collected in the dam zone. After utilization, it is discharged in the upper part of the reservoir. The impact exerted by the power plant on Rybnik Lake was discussed in many articles. The following topics were studied: thermal conditions in the reservoir (Kostecki 2005, Kowalski and Mazierski 2008); chromium, antimony and arsenic speciation (Loska et al. 2009, Jabłońska-Czapla et al. 2015, Jabłońska et al., 2012, Loska et al., 2003a; Loska et al. 2005, Widziewicz and Loska 2012); heavy metal contents (Loska and Wiechuła 2003b, Zemełka and Szalińska 2017, Loska et al. 1994; Jancewicz et al. 2012, Kostecki and Kowalski 2007) and PAH contents in the bottom sediments (Baran et al. 2017; Jancewicz et al. 2012) and metal bioaccumulation in the trophic chain (Kostecki 2007).

## Materials and methods

Indicators for the surface water quality in the reservoir (approx. 0.30 m layer) underwent statistical analysis. Their values were obtained between August 2002 and December 2017. Water was sampled monthly at three sampling points located close to the heated water discharge point, at the reservoir center and close to the dam and cooling water intake point. The sampling point location is presented in the figure (Fig. 1).

During the sampling, air temperature (AT), water temperature (WT) and 16 water quality indicators were measured. The indicators included: dissolved oxygen concentration (DO), Secchi disk visibility (SD), ammonium nitrogen concentration ($NH_4$), nitrate nitrogen concentration ($NO_3$), nitrite nitrogen concentration ($NO_2$), total nitrogen concentration (TN), phosphate phosphorus concentration ($PO_4$), total phosphorus concentration (TP), pH, chemical oxygen demand (COD), calcium concentration (Ca), magnesium concentration (Mg), chloride concentration (Cl), sulfate concentration ($SO_4$), total dissolved salt concentration (TDS) and electric conductivity coefficient (EC).

The Secchi disk visibility was read directly. The air and water temperature, dissolved oxygen concentration, pH and electric conductivity values were determined at the sampling site with the oxygen and conductivity meters. The collected water samples were transported to the laboratory at the temperature of 4°C. The determinations were carried


**Fig. 1.** The location sample points on the Rybnik reservoir (OpenStreetMap Foundation – OSMF)

out according to the methodology described in the Standard Methods (2017).

The statistical multivariate analysis was used to describe the correlations between the water quality indicators. The factor analysis methods (EFA and CFA) were applied. The calculations were implemented the R environment. (R Core Team, 2020)

Package psych (Revelle, 2020) were used in exploratory factor analysis and package sem were apply confirmatory factor analysis and exploratory structural equation modeling. (Fox at al. 2020)

## Result discussion

Before the factor analysis descriptive statistics for the analyzed variables were determined. The mean variable values, standard deviations and skewness and kurtosis values are presented in Table 3–5.

Many researchers in factor analysis have used raw data without performing any statistical tests or transforming the data. In order to (eliminate) avoid comparing data with different variances, some used variable standardization. The maximum-likelihood method requires assumptions about the normality of the data.

As it is seen the data are not normally distributed. Only four variables (i.e. AT, SD, Cl and EC) had normal distribution. For the remaining variables, the skewness and kurtosis coefficient values differed significantly from the values characteristic for the normal distribution. The situation particularly concerned the $NH_4$, $NO_2$, COD, Mg and $SO_4$ variables in all zones.

The normalization of the data using function bestNormalize (Peterson 2020) was partially successful: the values of skewness and kurtosis were significantly reduced, and most of the values did not fall outside the range (-1.1). However, the Anderson-Darling test (Korkmaz at al. 2020) showed that some variables did not meet the condition of normal distribution. This applies in particular to the variables DO, SD, $NO_3$, COD in the discharge zone, DO and TDS variables in the pelagic zone, and in the dam zone the variables DO, SD, $NO_3$ and $PO_4$. Also, the test based on Mardia's kurtosis showed that the variables do not satisfy the multivariate normal distribution condition. The best solution would be to use an asymptotically distribution-free (ADF) method. However, this method requires a large sample size (n> 5000) to correctly estimate the asymptotic covariance matrix. It was assumed that deviations from the multivariate normal distribution would not distort the results and the maximum likelihood method was used in the calculations.

At the initial stage, the correlation coefficient values between the variables were determined. They are given in Tables 6–8. The majority of the variables were weakly correlated. There was only a strong correlation between the AT (air temperature) and WT (water temperature) variables and between the Cl (chloride concentration), TDS (dissolved salt concentration) and EC (electrical conductivity) variables.

In the discharge zone, the variables AT and WT are weakly correlated with the variables $NO_3$ and pH, while in the pelagic and discharge zones they are also correlated with the variable SD. In the entire reservoir, the variable SD is weakly correlated with the variable pH, and in the dam zone also with the variable $NO_3$. In the discharge zone, the variable $NO_3$ is correlated with the variables TN and $PO_4$, while in the pelagic and dam zones it is also correlated with the variable $NO_2$. Throughout the reservoir, the variable TP correlates with the variable $PO_4$, but in the dam zone it is also correlated with the variable $SO_4$. The variables Ca, Mg, $SO_4$, TDS are also poorly correlated throughout the reservoir.

**Table 3.** Basic descriptive statistics of water quality indicators in discharge zone

| Variable | Mean value | Standard deviation | Minimum | Maximum | Skewness | Kurtosis | Skewness after normalization | Kurtosis after normalization |
|---|---|---|---|---|---|---|---|---|
| AT | 14.445 | 10.136 | -7.000 | 38.600 | 0.072 | -0.866 | 0.000 | -0.124 |
| WT | 20.154 | 7.265 | 3.300 | 34.500 | 0.042 | -1.175 | 0.000 | -0.124 |
| DO | 9.258 | 2.064 | 4.000 | 20.000 | 1.218 | 3.979 | 0.011 | 1.690 |
| SD | 1.148 | 0.901 | 0.200 | 1.300 | 10.908 | 140.519 | 0.008 | -0.121 |
| $NH_4$ | 0.552 | 0.447 | 0.010 | 3.810 | 3.203 | 15.889 | 0.030 | -0.236 |
| $NO_3$ | 1.522 | 1.007 | 0.010 | 5.760 | 0.674 | 0.433 | -0.190 | -0.510 |
| $NO_2$ | 0.064 | 0.074 | 0.002 | 0.857 | 6.508 | 61.290 | 0.005 | -0.132 |
| TN | 3.451 | 1.777 | 0.385 | 13.037 | 1.716 | 5.228 | 0.021 | 0.678 |
| $PO_4$ | 0.129 | 0.126 | 0.003 | 0.810 | 1.842 | 4.317 | -0.020 | -0.457 |
| TP | 0.391 | 0.298 | 0.003 | 2.192 | 2.340 | 8.883 | 0.053 | -0.362 |
| pH | 8.408 | 0.623 | 7.010 | 10.800 | 0.781 | 0.893 | 0.000 | -0.124 |
| COD | 35.990 | 29.908 | 8.660 | 337.720 | 5.883 | 49.925 | -0.080 | 1.184 |
| Ca | 72.342 | 27.701 | 4.280 | 194.000 | 1.645 | 3.959 | 0.000 | -0.123 |
| Mg | 16.888 | 4.886 | 6.700 | 57.140 | 3.256 | 21.52 | 0.000 | -0.123 |
| Cl | 221.056 | 76.712 | 104.200 | 467.030 | 0.728 | -0.584 | 0.000 | -0.124 |
| $SO_4$ | 119.386 | 39.504 | 67.100 | 364.800 | 3.885 | 18.149 | 0.000 | -0.123 |
| TDS | 688.847 | 157.270 | 380.000 | 1295.000 | 1.294 | 1.291 | 0.000 | -0.124 |
| EC | 1097.876 | 280.593 | 636.000 | 2200.000 | 1.005 | 0.610 | 0.000 | -0.123 |

**Table 4.** Basic descriptive statistics of water quality indicators in pelagic zone

| Variable | Mean value | Standard deviation | Minimum | Maximum | Skewness | Kurtosis | Skewness after normalization | Kurtosis after normalization |
|---|---|---|---|---|---|---|---|---|
| AT | 14.448 | 10.133 | -7.000 | 38.600 | 0.073 | -0.867 | 0.000 | -0.124 |
| WT | 17.208 | 7.933 | 3.400 | 32.500 | 0.141 | -1.349 | 0.000 | -0.125 |
| DO | 10.038 | 2.255 | 4.000 | 20.000 | 1.109 | 2.919 | 0.006 | 1.744 |
| SD | 1.294 | 0.441 | 0.450 | 2.750 | 0.459 | -0.071 | 0.022 | -0.312 |
| $NH_4$ | 0.471 | 0.388 | 0.000 | 3.670 | 3.791 | 23.977 | 0.012 | -0.139 |
| $NO_3$ | 1.477 | 0.954 | 0.029 | 3.500 | 0.160 | -1.157 | 0.001 | -0.130 |
| $NO_2$ | 0.065 | 0.107 | 0.003 | 1.030 | 6.670 | 50.683 | 0.015 | -0.152 |
| TN | 3.172 | 1.495 | 0.404 | 9.560 | 1.167 | 2.791 | 0.215 | 0.703 |
| $PO_4$ | 0.123 | 0.119 | 0.002 | 0.631 | 1.595 | 2.283 | -0.023 | -0.388 |
| TP | 0.377 | 0.229 | 0.032 | 1.354 | 1.292 | 1.745 | 0.064 | -0.474 |
| pH | 8.451 | 0.640 | 7.120 | 11.320 | 1.083 | 2.485 | 0.004 | -0.132 |
| COD | 33.389 | 19.019 | 8.660 | 139.000 | 3.198 | 13.854 | 0.002 | -0.122 |
| Ca | 70.054 | 23.866 | 9.000 | 191.000 | 1.995 | 6.464 | 0.000 | -0.124 |
| Mg | 16.211 | 3.462 | 8.800 | 28.000 | 0.739 | 0.663 | 0.000 | -0.123 |
| Cl | 220.382 | 73.013 | 98.920 | 480.000 | 0.723 | -0.526 | 0.000 | -0.125 |
| $SO_4$ | 114.917 | 31.106 | 73.850 | 345.000 | 4.232 | 25.171 | 0.000 | -0.123 |
| TDS | 712.488 | 212.841 | 460.000 | 1640.000 | 2.043 | 4.392 | 0.165 | -0.550 |
| EC | 1063.048 | 274.479 | 424.000 | 2150.000 | 1.122 | 1.393 | 0.000 | -0.123 |

**Table 5.** Basic descriptive statistics of water quality indicators in dam zone

| Variable | Mean value | Standard deviation | Minimum | Maximum | Skewness | Kurtosis | Skewness after normalization | Kurtosis after normalization |
|---|---|---|---|---|---|---|---|---|
| AT | 14.445 | 10.136 | -7.000 | 38.600 | 0.072 | -0.866 | 0.000 | -0.124 |
| WT | 16.727 | 7.899 | 4.000 | 31.000 | 0.066 | -1.356 | 0.022 | -0.261 |
| DO | 10.336 | 2.417 | 5.200 | 19.800 | 0.839 | 1.518 | -0.045 | 0.526 |
| SD | 1.449 | 0.532 | 0.500 | 3.400 | 0.446 | -0.055 | -0.436 | -0.303 |
| $NH_4$ | 0.578 | 0.790 | 0.020 | 7.280 | 5.355 | 34.801 | 0.090 | -0.211 |
| $NO_3$ | 1.425 | 0.974 | 0.000 | 3.900 | 0.335 | -0.912 | -0.052 | -1.062 |
| $NO_2$ | 0.067 | 0.097 | 0.002 | 0.870 | 5.914 | 42.643 | 0.013 | -0.156 |
| TN | 3.444 | 2.052 | 0.480 | 13.260 | 1.936 | 5.116 | 0.001 | -0.125 |
| $PO_4$ | 0.125 | 0.118 | 0.000 | 0.610 | 1.692 | 2.835 | 0.436 | -0.722 |
| TP | 0.432 | 0.312 | 0.050 | 1.970 | 2.080 | 5.813 | 0.103 | -0.668 |
| pH | 8.509 | 0.659 | 7.100 | 11.100 | 1.155 | 1.980 | 0.019 | -0.123 |
| COD | 32.304 | 17.106 | 6.500 | 182.100 | 3.708 | 26.703 | 0.002 | -0.123 |
| Ca | 70.047 | 21.42 | 22.200 | 163.000 | 1.487 | 2.751 | 0.000 | -0.125 |
| Mg | 16.945 | 3.877 | 9.200 | 34.300 | 1.331 | 2.599 | 0.003 | -0.127 |
| Cl | 220.474 | 77.499 | 106.000 | 458.000 | 0.748 | -0.513 | 0.000 | -0.123 |
| $SO_4$ | 118.686 | 41.949 | 68.400 | 356.200 | 3.789 | 16.515 | -0.002 | -0.128 |
| TDS | 693.062 | 156.393 | 247.000 | 1258.00 | 0.996 | 1.007 | 0.000 | -0.123 |
| EC | 1095.148 | 280.645 | 619.000 | 2130.00 | 0.890 | 0.245 | 0.000 | -0.124 |

Another important condition for the success of factor analysis is factorability (it is a measure of the adequacy of the selection of input variables for factor analysis).

In Bartlett's test the hypothesis that observed correlation matrix is an identity matrix is verified, which would indicate that the variables are unrelated and therefore unsuitable for structure detection. Essentially it checks to see if there is a certain redundancy between the variables that we can summarize with a few number of factors.

A better tests checks if the data contained in the data set are sufficiently correlated with each other. If the correlations are weak, they are unlikely to form strong and easy to interpret factors. The minimum acceptable value is 0.50, but most authors recommend a value of at 0.60 before undertaking

**Table 6.** Correlation matrix for discharge zone

| | AT | WT | DO | SD | $NH_4$ | $NO_3$ | $NO_2$ | TN | $PO_4$ | TP | pH | COD | Ca | Mg | Cl | $SO_4$ | TDS | EC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1.00 | | | | | | | | | | | | | | | | | |
| WT | **0.79** | 1.00 | | | | | | | | | | | | | | | | |
| H | -0.19 | -0.25 | 1.00 | | | | | | | | | | | | | | | |
| SD | *-0.38* | *-0.38* | -0.03 | 1.00 | | | | | | | | | | | | | | |
| $NH_4$ | -0.12 | -0.06 | -0.15 | -0.02 | 1.00 | | | | | | | | | | | | | |
| $NO_3$ | *-0.44* | *-0.46* | 0.15 | *0.30* | 0.28 | 1.00 | | | | | | | | | | | | |
| $NO_2$ | -0.12 | -0.03 | -0.16 | 0.01 | 0.18 | 0.36 | 1.00 | | | | | | | | | | | |
| TN | -0.27 | *-0.30* | 0.14 | 0.10 | *0.34* | ***0.67*** | 0.29 | 1.00 | | | | | | | | | | |
| $PO_4$ | 0.06 | 0.17 | -0.32 | -0.08 | -0.04 | ***-0.50*** | -0.17 | *-0.39* | 1.00 | | | | | | | | | |
| TP | 0.12 | 0.29 | -0.20 | 0.02 | 0.06 | *-0.38* | -0.14 | *-0.34* | ***0.55*** | 1.00 | | | | | | | | |
| pH | ***0.50*** | ***0.52*** | 0.15 | *-0.44* | -0.15 | *-0.35* | -0.24 | *-0.34* | 0.06 | 0.28 | 1.00 | | | | | | | |
| COD | 0.10 | 0.16 | 0.11 | -0.07 | 0.05 | -0.18 | -0.04 | -0.22 | 0.05 | 0.22 | 0.24 | 1.00 | | | | | | |
| Ca | 0.10 | -0.04 | -0.01 | -0.09 | -0.22 | -0.17 | -0.26 | -0.06 | 0.05 | -0.19 | -0.03 | *-0.32* | 1.00 | | | | | |
| Mg | 0.03 | -0.08 | -0.01 | -0.17 | -0.02 | 0.07 | -0.05 | 0.15 | -0.07 | *-0.36* | -0.05 | -0.18 | *0.47* | 1.00 | | | | |
| Cl | 0.03 | -0.12 | -0.01 | -0.19 | -0.10 | -0.13 | *-0.31* | 0.07 | 0.06 | -0.21 | -0.05 | -0.22 | *0.61* | *0.47* | 1.00 | | | |
| $SO_4$ | -0.12 | -0.23 | -0.02 | -0.09 | -0.03 | 0.14 | -0.12 | 0.21 | -0.02 | -0.20 | -0.14 | *-0.32* | ***0.51*** | *0.43* | ***0.64*** | 1.00 | | |
| TDS | -0.04 | -0.14 | -0.08 | -0.10 | -0.09 | -0.05 | -0.19 | 0.11 | 0.06 | -0.22 | -0.09 | -0.20 | ***0.56*** | ***0.51*** | **0.79** | ***0.54*** | 1.00 | |
| EC | 0.03 | -0.17 | 0.01 | -0.13 | -0.14 | -0.12 | -0.28 | 0.06 | 0.01 | -0.27 | -0.15 | -0.21 | ***0.63*** | *0.43* | **0.88** | ***0.62*** | **0.82** | 1.00 |

**strong > 0.75**
***moderate 0.75–0.50***
*weak 0.50–0.30*

**Table 7.** Correlation matrix for pelagic zone

| | AT | WT | DO | SD | $NH_4$ | $NO_3$ | $NO_2$ | TN | $PO_4$ | TP | pH | COD | Ca | Mg | Cl | $SO_4$ | TDS | EC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1.00 | | | | | vb | | | | | | | | | | | | |
| WT | **0.84** | 1.00 | | | | | | | | | | | | | | | | |
| DO | -0.11 | -0.19 | 1.00 | | | | | | | | | | | | | | | |
| SD | *-0.45* | *-0.42* | -0.07 | 1.00 | | | | | | | | | | | | | | |
| $NH_4$ | -0.13 | -0.17 | -0.11 | 0.01 | 1.00 | | | | | | | | | | | | | |
| $NO_3$ | *-0.43* | *-0.42* | 0.12 | *0.31* | *0.32* | 1.00 | | | | | | | | | | | | |
| $NO_2$ | -0.13 | -0.12 | -0.15 | 0.05 | *0.38* | *0.42* | 1.00 | | | | | | | | | | | |
| TN | -0.30 | -0.30 | 0.02 | 0.21 | *0.35* | ***0.65*** | *0.33* | 1.00 | | | | | | | | | | |
| $PO_4$ | 0.10 | 0.13 | *-0.35* | -0.13 | -0.08 | ***-0.55*** | -0.15 | *-0.49* | 1.00 | | | | | | | | | |
| TP | 0.10 | 0.17 | -0.25 | -0.11 | -0.04 | *-0.35* | -0.13 | *-0.40* | ***0.62*** | 1.00 | | | | | | | | |
| pH | ***0.51*** | ***0.56*** | 0.14 | *-0.47* | -0.14 | *-0.35* | -0.22 | *-0.37* | 0.17 | 0.21 | 1.00 | | | | | | | |
| COD | 0.04 | 0.09 | 0.07 | -0.18 | 0.17 | -0.02 | 0.04 | -0.13 | 0.05 | 0.23 | 0.36 | 1.00 | | | | | | |
| Ca | 0.10 | 0.10 | -0.08 | -0.02 | -0.26 | -0.25 | -0.19 | 0.01 | 0.10 | -0.14 | -0.11 | *-0.32* | 1.00 | | | | | |
| Mg | 0.06 | 0.08 | -0.03 | -0.06 | 0.06 | -0.13 | 0.12 | -0.04 | 0.09 | -0.25 | -0.02 | -0.06 | ***0.50*** | 1.00 | | | | |
| Cl | 0.01 | -0.05 | 0.04 | -0.04 | -0.08 | -0.19 | -0.20 | 0.07 | 0.06 | -0.22 | -0.17 | -0.23 | ***0.64*** | ***0.53*** | 1.00 | | | |
| $SO_4$ | -0.01 | -0.05 | -0.03 | 0.10 | 0.05 | 0.08 | -0.01 | 0.25 | -0.13 | -0.29 | -0.14 | -0.27 | *0.49* | *0.46* | ***0.55*** | 1.00 | | |
| TDS | 0.07 | 0.02 | -0.04 | -0.09 | -0.01 | -0.24 | -0.13 | 0.05 | 0.09 | -0.21 | -0.08 | *-0.32* | ***0.58*** | ***0.57*** | **0.78** | ***0.54*** | 1.00 | |
| EC | 0.02 | -0.04 | -0.05 | 0.03 | -0.06 | -0.20 | -0.18 | 0.03 | 0.07 | -0.18 | -0.11 | -0.21 | ***0.52*** | *0.41* | **0.76** | ***0.52*** | ***0.59*** | 1.00 |

**strong > 0.75**
***moderate 0.75–0.50***
*weak 0.50–0.30*

**Table 8.** Correlation matrix for dam zone

| | AT | WT | DO | SD | $NH_4$ | $NO_3$ | $NO_2$ | TN | $PO_4$ | TP | pH | COD | Ca | Mg | Cl | $SO_4$ | TDS | EC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1.00 | | | | | | | | | | | | | | | | | |
| WT | **0.89** | 1.00 | | | | | | | | | | | | | | | | |
| DO | -0.04 | -0.09 | 1.00 | | | | | | | | | | | | | | | |
| SD | *-0.49* | *-0.42* | -0.14 | 1.00 | | | | | | | | | | | | | | |
| $NH_4$ | -0.21 | -0.23 | -0.08 | 0.12 | 1.00 | | | | | | | | | | | | | |
| $NO_3$ | *-0.47* | *-0.48* | 0.10 | *0.42* | *0.39* | 1.00 | | | | | | | | | | | | |
| $NO_2$ | -0.20 | -0.17 | -0.20 | 0.22 | 0.33 | *0.45* | 1.00 | | | | | | | | | | | |
| TN | -0.31 | -0.37 | 0.12 | 0.22 | *0.43* | **0.71** | 0.39 | 1.00 | | | | | | | | | | |
| $PO_4$ | 0.09 | 0.17 | *-0.31* | -0.15 | -0.06 | ***-0.53*** | -0.15 | *-0.45* | 1.00 | | | | | | | | | |
| TP | 0.09 | 0.18 | -0.21 | -0.03 | -0.03 | -0.27 | -0.09 | *-0.41* | *0.42* | 1.00 | | | | | | | | |
| pH | ***0.55*** | ***0.55*** | 0.12 | ***-0.55*** | -0.26 | *-0.44* | *-0.32* | -0.38 | 0.16 | 0.21 | 1.00 | | | | | | | |
| COD | 0.12 | 0.10 | 0.06 | *-0.31* | 0.01 | -0.11 | -0.04 | -0.21 | 0.12 | *0.30* | *0.36* | 1.00 | | | | | | |
| Ca | 0.04 | 0.01 | 0.13 | 0.02 | -0.23 | -0.17 | -0.19 | 0.02 | 0.03 | *-0.33* | -0.14 | *-0.41* | 1.00 | | | | | |
| Mg | 0.01 | 0.03 | 0.25 | -0.03 | 0.01 | 0.04 | 0.06 | 0.20 | -0.08 | *-0.39* | -0.09 | -0.19 | *0.45* | 1.00 | | | | |
| Cl | 0.06 | 0.01 | 0.19 | -0.06 | -0.11 | -0.22 | -0.21 | 0.06 | 0.02 | *-0.34* | -0.06 | -0.29 | ***0.63*** | ***0.57*** | 1.00 | | | |
| $SO_4$ | -0.11 | -0.13 | 0.18 | 0.15 | 0.00 | 0.11 | 0.01 | 0.22 | -0.12 | *-0.40* | -0.18 | *-0.34* | ***0.54*** | *0.45* | *0.60* | 1.00 | | |
| TDS | 0.05 | 0.04 | 0.04 | 0.01 | -0.01 | -0.24 | -0.14 | 0.02 | 0.12 | *-0.32* | -0.01 | -0.28 | ***0.61*** | *0.43* | **0.74** | *0.49* | 1.00 | |
| EC | 0.02 | -0.02 | 0.19 | 0.00 | -0.10 | -0.20 | -0.18 | 0.08 | 0.00 | *-0.40* | -0.16 | *-0.33* | ***0.61*** | *0.44* | **0.83** | *0.58* | **0.76** | 1.00 |

**strong > 0.75**
***moderate 0.75–0.50***
*weak 0.50–0.30*

a factor analysis. You can also determine the adequacy of each variable ($MSA_h$) and eliminate the variable with a very low $MSA_h$ if necessary. The results of the calculations are presented in table 9 The determined KMO value was above 0.7 whereas the Bartlett's test was insignificant, which showed that the variables were statistically significantly correlated. The finding proved the purposefulness in applying the factor analysis.

The Cattell method and the Kaiser method are among the most frequently used methods of determining the number of factors. The correlation matrix eigenvalues are the basis for both tests. According to the factor scree plot, the number of factor is determined on the basis of where the „elbow" point of the eigenvalues in the graph is located. The Kaiser criterion indicates that the factors with eigenvalues higher than 1 ought to be used for further analysis.

The great advantage of these methods is their ease of use. An interesting alternative to these methods are parallel analysis, and very simple structure.

Parallel analysis is similar to Cattell method but in contrary to Kaiser criterion the factors with eigenvalues higher than eigenvalues of random data with the same properties ought to be used for further analysis.

The vss function compares the fit of a series of factor analyzes with a simplified load matrix containing only the greatest loadings. In system R the vss function included Velicer's Minimum Average. Partial (MAP Velicer) test is based on PCA analysis. Next, successive components are removed from the correlation matrix and the mean of square partial correlations is determined. The number of factors for factor analysis is determined by the point at which the minimum mean squared of the partial correlations is obtained.

In the Table 10 the determined the factors number proposed by the selected methods are presented.

As can be seen, depending on the calculation method and the zone of the reservoir, the number of proposed factors is in the range of 3–5. In order to ensure the comparability of the results and to avoid difficulties during further calculations, a four-factor model was chosen.

In order to obtain a transparent load system and to determine the correlation between the factors, the data was subjected to the maximum likelihood method with geominQ rotation was used. The results are presented in Table 11–13. According to the accepted convention, factor loadings above 0.75 were called "strong", for factor loadings in the range 0,75–0,50 and 0,5–0,3 the terms 'moderate', and 'weak' were applied respectively (Liu et al. 2003).

In all sampling points in the discharge, pelagic and dam zones, the first factor a highly affected by Cl, TDS and EC, moderately affected by Mg and $SO_4$ and weakly by TP and COD, represents the water salinity. Depending on the zone, the factor salinity defines from 20.0 to 23.5% of the total variance.

The factor represents the thermal conditions is strongly correlated with the variables AT, WT, weakly with pH, SD. In the heated water discharge zone and in the pelagic zone, temperature factor describes 18.4% and 19.7% of the variance, respectively, while in the dam zone describes only 7.5% of the variance.

In the discharge zone, factor (ML 3) contains $NO_3$ and TN with strong positively loadings and $NH_4$, $NO_2$ with weakly positively loadings, while $PO_4$ and TP with negatively weakly loadings. It described 7.65% of the total variance. Factor ML4 is moderately positively correlated with phosphorus compounds (PO4, TP) and moderately negatively correlated with DO. This factor describe 5.13% of the total variance.

In the pelagic zone, phosphorus factor (ML 3) is strongly correlated with $PO_4$, moderately correlated with TP, $NO_2$, and weakly with DO, $NO_3$, TN, describing 8.47% of the total variance. The nitrogen factor (ML 4) describe 5.56% of the variability was on average associated with the variables $NH_4$, $NO_2$, TN and weakly with the variable $NO_3$.

In the dam zone (ML 3), factor was strongly correlated with $NO_3$, TN and $PO_4$ and weakly with TP describes 20.98% of the total variance, this factor represents nutrient concentrations. Factor ML4 describe 4.74% of the variance, it had moderate factor loadings for DO, and weak for SD, $NO_2$, pH, and is associated with the phenomenon of eutrophication.

Considering the correlations between latent variables, it can be noticed that the "*salinity*" variable is not correlated with any variables. In the discharge zone, the variables "*temperature*" and "*nitrogen*" are correlated. In the pelagic zone "*temperature*" is correlated with the "*phosphorus*" and this is correlated with "*nitrogen*". The variables "*temperature*" and "*nutrient"* are correlated in the dam zone.

**Table 9.** Bartlett and Kaiser-Meyer-Olkin test result

| Reservoir zone | Bartlett test | | | KMO test |
|---|---|---|---|---|
| | $\chi^2$ | df | p value | MSA value |
| Discharge | 1970.214 | 153 | 0.0000 | 0.77 |
| Pelagic | 1893.310 | 153 | 0.0000 | 0.76 |
| Dam | 2091.250 | 153 | 0.0000 | 0.79 |

**Table 10.** Determination of factors number

| Reservoir zone | Paralel analysis | VSS | Velicer MAP |
|---|---|---|---|
| Discharge | 4 | 3 / 4 | 3 |
| Pelagic | 5 | 3 / 5 | 5 |
| Dam | 5 | 2 / 4 | 3 |

**Table 11.** Rotated factor loadings matrix for discharge zone (ML; geominQ rotation)

| Variable | salinity ML 1 | temperature ML 2 | nitrogen ML 3 | phosphorus ML 4 |
|---|---|---|---|---|
| AT | 0.103 | **0.874** | -0.002 | -0.028 |
| WT | -0.058 | **0.934** | 0.011 | 0.172 |
| DO | -0.070 | -0.207 | -0.024 | ***-0.506*** |
| SD | -0.195 | *-0.442* | 0.037 | 0.031 |
| $NH_4$ | -0.076 | 0.011 | *0.369* | 0.270 |
| $NO_3$ | -0.062 | -0.248 | **0.756** | -0.103 |
| $NO_2$ | -0.226 | 0.046 | *0.467* | 0.141 |
| TN | 0.160 | -0.050 | **0.765** | 0.027 |
| $PO_4$ | 0.009 | -0.092 | ***-0.568*** | ***0.642*** |
| TP | -0.285 | 0.041 | *-0.434* | *0.462* |
| pH | -0.098 | *0.494* | -0.217 | -0.152 |
| COD | -0.275 | 0.063 | -0.214 | -0.074 |
| Ca | ***0.667*** | 0.058 | -0.104 | -0.057 |
| Mg | ***0.544*** | 0.090 | 0.185 | -0.042 |
| Cl | **0.926** | 0.028 | -0.052 | 0.016 |
| $SO_4$ | ***0.687*** | -0.073 | 0.153 | 0.063 |
| TDS | **0.866** | 0.001 | 0.024 | 0.085 |
| EC | **0.937** | -0.015 | -0.061 | -0.051 |
| eigenvalues | 4.1224 | 3.3215 | 1.3770 | 0.9235 |
| % variance | 22.9022 | 18.4530 | 7.6498 | 5.1304 |
| % cumulative | 22.9022 | 41.3552 | 49.0050 | 54.1354 |

**strong > 0.75**; ***moderate 0.75–0.50***; *weak 0.50–0.30*

**Table 12.** Rotated factor loadings matrix for pelagic zone (ML; geominQ rotation)

| variable | salinity ML 2 | temperature ML 1 | phosphorus ML 3 | nitogen ML 4 |
|---|---|---|---|---|
| AT | 0.039 | **0.899** | -0.041 | -0.022 |
| WT | -0.018 | **0.945** | 0.014 | 0.036 |
| DO | -0.026 | -0.140 | *-0.478* | *-0.452* |
| SD | -0.011 | *-0.435* | -0.034 | 0.109 |
| $NH_4$ | -0.040 | -0.033 | 0.057 | ***0.518*** |
| $NO_3$ | -0.149 | -0.191 | *-0.451* | *0.461* |
| $NO_2$ | -0.118 | 0.048 | -0.006 | ***0.617*** |
| TN | 0.147 | -0.072 | *-0.403* | ***0.520*** |
| $PO_4$ | 0.005 | -0.155 | **0.965** | 0.014 |
| TP | *-0.311* | -0.051 | ***0.693*** | -0.020 |
| pH | -0.189 | ***0.519*** | 0.028 | -0.254 |
| COD | *-0.324* | 0.074 | 0.067 | -0.048 |
| Ca | ***0.705*** | 0.048 | 0.037 | -0.055 |
| Mg | ***0.618*** | 0.080 | 0.069 | 0.145 |
| Cl | **0.913** | -0.085 | -0.017 | -0.085 |
| $SO_4$ | ***0.669*** | 0.029 | -0.145 | 0.184 |
| TDS | **0.835** | 0.006 | 0.045 | 0.010 |
| EC | **0.773** | -0.076 | 0.020 | -0.073 |
| eigenvalue | 3.7630 | 3.5396 | 1.52424 | 1.0023 |
| % variance | 20.9053 | 19.6644 | 8.4680 | 5.5683 |
| % cumulative | 20.9053 | 40.5697 | 49.0377 | 54.6060 |

**strong > 0.75**; ***moderate 0.75–0.50***; *weak 0.50–0.30*

**Table 13.** Rotated factor loadings matrix for dam zone (ML; geominQ rotation)

| variable | salinity ML 2 | nutrient ML 3 | temperature ML 1 | eutrophic ML 4 |
|---|---|---|---|---|
| AT | 0.050 | 0.026 | **0.957** | -0.015 |
| WT | 0.014 | -0.069 | **0.921** | 0.053 |
| DO | 0.078 | *0.457* | -0.056 | *-0.565* |
| SD | 0.078 | -0.026 | -0.372 | *0.459* |
| $NH_4$ | -0.058 | 0.234 | -0.054 | 0.289 |
| $NO_3$ | -0.156 | **0.720** | -0.139 | 0.279 |
| $NO_2$ | -0.098 | 0.240 | 0.031 | *0.463* |
| TN | 0.138 | **0.700** | -0.009 | 0.251 |
| $PO_4$ | 0.019 | **-0.733** | -0.130 | 0.064 |
| TP | -0.434 | *-0.488* | -0.048 | 0.015 |
| pH | -0.211 | -0.030 | *0.440* | *-0.472* |
| COD | *-0.449* | -0.015 | 0.020 | -0.366 |
| Ca | **0.722** | -0.050 | 0.003 | 0.018 |
| Mg | *0.563* | 0.257 | 0.097 | -0.043 |
| Cl | **0.889** | 0.004 | -0.004 | -0.117 |
| $SO_4$ | *0.668* | 0.201 | -0.040 | 0.050 |
| TDS | **0.824** | -0.129 | 0.003 | 0.038 |
| EC | **0.896** | -0.023 | -0.032 | -0.039 |
| eigenvalues | 4.2282 | 3.7764 | 1.3542 | 0.8529 |
| % variance | 23.4900 | 20.9802 | 7.5234 | 4.7385 |
| % cumulative | 23.4900 | 44.4702 | 51.9936 | 56.7321 |

**strong > 0.75**; ***moderate 0.75–0.50***; *weak 0.50–0.30*

The EFA results helped to distinguish groups of observable variables related to salinity, thermal conditions, the content of nitrogen and phosphorus compounds and the threat of eutrophication. It can be assumed that the mentioned groups of variables corresponded to the following unobservable variables: *salinity, temperature, nitrogen, phosphorus, nutrient, eutrophic*.

Taking into account the results of exploratory factor analysis, a model for discharge zone was proposed in which correlations between latent variables were adopted: *temperature – nitrogen* and *phosphorus – nitrogen*. The obtained results are presented in Table 14: chi-square = 235.68, df = 63, chi-square / df = 3.74, GFI = 0.861, AGFI = 0.799, RMSEA = 0.1147, CFI = 0.8917, and SRMR = 0.109, AIC = 291.68, BIC = -100.89.

Similarly, based on the EFA results, a CFA model for the pelagic zone was proposed (TABLE 15). The model fit indices were as follows: chi-square = 392.86, df = 117, chi-square / df = 3.36, GFI = 0.820, AGFI = 0.765, RMSEA = 0.1064, CFI = 0.841, SRMR = 0.103, AIC = 464.86, BIC = -232.20.

In dam zone EFA model was verified with CFA (TABLE 16), obtaining the following fit ratios: chi-square = 347.83, df = 100, chi-square / df = 3.47, GFI = 0.833, AGFI = 0.773, RMSEA = 0.1092, CFI = 0.868, SRMR = 0.098, AIC = 419.83, BIC = -186.40.

## Conclusions

Water quality in the researched reservoir depends on the quality of water that supplies the reservoir and quality of the wastewater discharged from the power plant into the reservoir. The reservoir is subject to strong anthropopressure as it is utilized as a cooling pond.

1. The factor analysis application helped to distinguish four factors defining the reservoir water quality. In the entire reservoir, the salinity factor comprised of variables like Ca, Mg, Cl, $SO_4$ TDS, EC described from 20.0 to 23.5% of the total variance respectively. The factor called the temperature factor that was correlated with AT, WT, SD, pH in the discharge and pelagic zones described 18.4% and 19.7% of the total variance, respectively, In the dam zone temperature factor explain only 7.5% of the total variance. In the discharge zone, factor called the nitrogen factor explained 7.65% of the total variance (comprised of variables like $NO_3$, TN) and the factor correlated with phosphorus compounds 5.13% of the variance. In the pelagic zone the factor related to phosphorus factor explain 8.47% of the variance, and the nitrogen factor explain 5.57% of the variance. In the dam zone, the factors called the nutrient factor comprised of variables like $NO_3$,TN, $PO_4$, TP explained 7.52% of the variation, the factor

**Table 14.** Estimated parameters for the corrected CFA model of discharge zone

| Estimate | Std. Error | z value | Pr(>\|z\|) | |
|---|---|---|---|---|
| 0,6692 | 0,0622 | 10,7534 | 0,0000 | Ca <--- salinity |
| 0,5137 | 0,0660 | 7,7839 | 0,0000 | Mg <--- salinity |
| 0,9280 | 0,0530 | 17,5051 | 0,0000 | Cl <--- salinity |
| 0,6722 | 0,0621 | 10,8177 | 0,0000 | $SO_4$ <--- salinity |
| 0,8590 | 0,0558 | 15,3921 | 0,0000 | TDS <--- salinity |
| 0,9435 | 0,0524 | 18,0235 | 0,0000 | EC <--- salinity |
| 0,8926 | 0,0595 | 14,9986 | 0,0000 | AT <--- temperature |
| 0,8843 | 0,0579 | 14,8076 | 0,0000 | WT <--- temperature |
| 0,5758 | 0,0666 | 8,6495 | 0,0000 | pH <--- temperature |
| 0,9342 | 0,0632 | 14,7728 | 0,0000 | $NO_3$ <--- nitrogen |
| 0,6767 | 0,0662 | 10,2205 | 0,0000 | TN <--- nitrogen |
| 0,9255 | 0,0864 | 10,7061 | 0,0000 | $PO_4$ <--- phosphorus |
| 0,5987 | 0,0770 | 7,7789 | 0,0000 | TP <--- phosphorus |
| 0,5507 | 0,0564 | 9,7630 | 0,0000 | Ca <--> Ca |
| 0,7346 | 0,0734 | 10,0073 | 0,0000 | Mg <--> Mg |
| 0,1374 | 0,0214 | 6,4322 | 0,0000 | Cl <--> Cl |
| 0,5466 | 0,0560 | 9,7556 | 0,0000 | $SO_4$ <--> $SO_4$ |
| 0,2606 | 0,0302 | 8,6253 | 0,0000 | TDS <--> TDS |
| 0,1083 | 0,0199 | 5,4423 | 0,0000 | EC <--> EC |
| 0,2232 | 0,0452 | 4,9350 | 0,0000 | AT <--> AT |
| 0,2088 | 0,0452 | 4,6241 | 0,0000 | WT <--> WT |
| 0,7798 | 0,0789 | 9,8844 | 0,0000 | SD <--> SD |
| 0,6466 | 0,0679 | 9,5233 | 0,0000 | pH <--> pH |
| 0,9149 | 0,0904 | 10,1241 | 0,0000 | $NH_4$ <--> $NH_4$ |
| 0,0708 | 0,0626 | 1,1306 | 0,2582 | $NO_3$ <--> $NO_3$ |
| 0,8602 | 0,0855 | 10,0580 | 0,0000 | $NO_2$ <--> $NO_2$ |
| 0,5111 | 0,0603 | 8,4691 | 0,0000 | TN <--> TN |
| 0,8895 | 0,0893 | 9,9634 | 0,0000 | DO <--> DO |
| 0,1366 | 0,1078 | 1,2664 | 0,2054 | $PO_4$ <--> $PO_4$ |
| 0,6399 | 0,0776 | 8,2490 | 0,0000 | TP <--> TP |
| -0,4705 | 0,0569 | -8,2703 | 0,0000 | nitrogen <--> temperature |
| -0,5261 | 0,0652 | -8,0716 | 0,0000 | phosphorus <--> nitrogen |

Model Chisquare = 235.68 Df = 63 Pr(>Chisq) = 9.0872e-22
Goodness-of-fit index = 0.86087
Adjusted goodness-of-fit index = 0.79904
RMSEA index = 0.11479 90% CI: (NA, NA)
Bentler-Bonett NFI = 0.85903
Bentler CFI = 0.89166
SRMR = 0.10957
AIC = 291.68
BIC = -100.89

**Table 15.** Estimated parameters for the CFA model of pelagic zone

| Estimate | Std, Error | z value | Pr(>\|z\|) | |
|---|---|---|---|---|
| 0,6972 | 0,0622 | 11,2144 | 0,0000 | Ca <--- salinity |
| 0,6054 | 0,0647 | 9,3527 | 0,0000 | Mg <--- salinity |
| 0,9298 | 0,0539 | 17,2397 | 0,0000 | Cl <--- salinity |
| 0,6292 | 0,0641 | 9,8158 | 0,0000 | $SO_4$ <--- salinity |
| 0,8276 | 0,0579 | 14,2915 | 0,0000 | TDS <--- salinity |
| 0,7838 | 0,0594 | 13,1959 | 0,0000 | EC <--- salinity |
| 0,9087 | 0,0564 | 16,1008 | 0,0000 | AT <--- temperature |
| 0,9154 | 0,0562 | 16,2847 | 0,0000 | WT <--- temperature |
| -0,4927 | 0,0676 | -7,2911 | 0,0000 | SD <--- temperature |
| 0,6007 | 0,0650 | 9,2394 | 0,0000 | pH <--- temperature |
| -0,3371 | 0,0680 | -4,9586 | 0,0000 | DO <---phosphorus |
| 1,0501 | 0,0753 | 13,9475 | 0,0000 | $PO_4$ <--- phosphorus |
| 0,5848 | 0,0709 | 8,2499 | 0,0000 | TP <--- phosphorus |
| 0,3540 | 0,0712 | 4,9701 | 0,0000 | $NH_4$ <--- nitrogen |
| 0,8850 | 0,0577 | 15,3349 | 0,0000 | $NO_3$ <--- nitrogen |
| 0,4284 | 0,0696 | 6,1530 | 0,0000 | $NO_2$ <--- nitrogen |
| 0,7048 | 0,0628 | 11,2151 | 0,0000 | TN <--- nitrogen |
| 0,1725 | 0,0389 | 4,4358 | 0,0000 | AT <--> AT |
| 0,1601 | 0,0388 | 4,1263 | 0,0000 | WT <--> WT |
| 0,8864 | 0,0871 | 10,1715 | 0,0000 | DO <--> DO |
| 0,7572 | 0,0765 | 9,9030 | 0,0000 | SD <--> SD |
| 0,8674 | 0,0869 | 9,9803 | 0,0000 | $NH_4$ <--> $NH_4$ |
| 0,1686 | 0,0543 | 3,1033 | 0,0019 | $NO_3$ <--> $NO_3$ |
| 0,7995 | 0,0812 | 9,8432 | 0,0000 | $NO_2$ <--> $NO_2$ |
| 0,4742 | 0,0582 | 8,1540 | 0,0000 | TN <--> TN |
| -0,1028 | 0,1249 | -0,8230 | 0,4105 | $PO_4$ <--> $PO_4$ |
| 0,6580 | 0,0747 | 8,8055 | 0,0000 | TP <--> TP |
| 0,6361 | 0,0658 | 9,6710 | 0,0000 | pH <--> pH |
| 0,5119 | 0,0546 | 9,3803 | 0,0000 | Ca <--> Ca |
| 0,6319 | 0,0651 | 9,7081 | 0,0000 | Mg <--> Mg |
| 0,1338 | 0,0286 | 4,6695 | 0,0000 | Cl <--> Cl |
| 0,6023 | 0,0625 | 9,6406 | 0,0000 | $SO_4$ <--> $SO_4$ |
| 0,3151 | 0,0385 | 8,1876 | 0,0000 | TDS <--> TDS |
| 0,3843 | 0,0438 | 8,7709 | 0,0000 | EC <--> EC |
| -0,4473 | 0,0559 | -7,9985 | 0,0000 | nitrogen <--> temperaturę |
| -0,5337 | 0,0595 | -8,9742 | 0,0000 | nitrogen <--> phosphorus |

Model Chisquare = 392.8577 Df = 117 Pr(>Chisq) = 1.629166e-31
Goodness-of-fit index = 0.8206204
Adjusted goodness-of-fit index = 0.7654267
RMSEA index = 0.1064677
Bentler-Bonett NFI = 0.7895314
Bentler CFI = 0.8405987
SRMR = 0.1036853
AIC = 464.8577
BIC = -232.1954

**Table 16.** Estimated parameters for the CFA model of dam zone

| Estimate | Std, Error | z value | Pr(>\|z\|) | |
|---|---|---|---|---|
| -0,4869 | 0,0630 | -7,7334 | 0,0000 | TP <--- salinity |
| -0,3683 | 0,0691 | -5,3323 | 0,0000 | COD <--- salinity |
| 0,7113 | 0,0614 | 11,5754 | 0,0000 | Ca <--- salinity |
| 0,5714 | 0,0652 | 8,7591 | 0,0000 | Mg <--- salinity |
| 0,9099 | 0,0542 | 16,7933 | 0,0000 | Cl <--- salinity |
| 0,6591 | 0,0630 | 10,4643 | 0,0000 | $SO_4$ <--- salinity |
| 0,8189 | 0,0578 | 14,1735 | 0,0000 | TDS <--- salinity |
| 0,8996 | 0,0546 | 16,4718 | 0,0000 | EC <--- salinity |
| 0,9358 | 0,0585 | 15,9888 | 0,0000 | $NO_3$ <--- nutrient |
| 0,7600 | 0,0627 | 12,1126 | 0,0000 | TN <--- nutrient |
| -0,5716 | 0,0669 | -8,5420 | 0,0000 | $PO_4$ <--- nutrient |
| -0,4129 | 0,0629 | -6,5682 | 0,0000 | TP <--- nutrient |
| 0,9484 | 0,0553 | 17,1567 | 0,0000 | AT <--- temperature |
| 0,9208 | 0,0552 | 16,6722 | 0,0000 | WT <--- temperature |
| -0,6704 | 0,0688 | -9,7471 | 0,0000 | SD <--- eutrophic |
| -0,4017 | 0,0739 | -5,4350 | 0,0000 | $NO_2$ <--- eutrophic |
| 0,7920 | 0,0671 | 11,8025 | 0,0000 | pH <--- eutrophic |
| 0,0986 | 0,0400 | 2,4615 | 0,0138 | AT <--> AT |
| 0,1282 | 0,0387 | 3,3112 | 0,0009 | WT <--> WT |
| 0,5505 | 0,0687 | 8,0148 | 0,0000 | SD <--> SD |
| 0,1243 | 0,0518 | 2,3997 | 0,0164 | $NO_3$ <--> $NO_3$ |
| 0,8335 | 0,0858 | 9,7096 | 0,0000 | $NO_2$ <--> $NO_2$ |
| 0,4208 | 0,0540 | 7,7939 | 0,0000 | TN <--> TN |
| 0,6733 | 0,0704 | 9,5654 | 0,0000 | $PO_4$ <--> $PO_4$ |
| 0,6404 | 0,0665 | 9,6278 | 0,0000 | TP <--> TP |
| 0,3583 | 0,0665 | 5,3857 | 0,0000 | pH <--> pH |
| 0,8618 | 0,0855 | 10,0830 | 0,0000 | COD <--> COD |
| 0,4922 | 0,0522 | 9,4368 | 0,0000 | Ca <--> Ca |
| 0,6709 | 0,0682 | 9,8407 | 0,0000 | Mg <--> Mg |
| 0,1703 | 0,0264 | 6,4425 | 0,0000 | Cl <--> Cl |
| 0,5635 | 0,0585 | 9,6295 | 0,0000 | $SO_4$ <--> $SO_4$ |
| 0,3279 | 0,0379 | 8,6570 | 0,0000 | TDS <--> TDS |
| 0,1891 | 0,0275 | 6,8659 | 0,0000 | EC <--> EC |
| -0,5046 | 0,0584 | -8,6395 | 0,0000 | nutrient <--> temperature |
| -0,6246 | 0,0615 | -10,1537 | 0,0000 | eutrophic <--> nutrient |
| 0,7140 | 0,0518 | 13,7944 | 0,0000 | eutrophic <--> temperature |

Model Chisquare = 347.8332 Df = 100 Pr(>Chisq) = 4.01768e-29
Goodness-of-fit index = 0.8331115
Adjusted goodness-of-fit index = 0.7730316
RMSEA index = 0.1091561 90% CI: (NA, NA)
Bentler-Bonett NFI = 0.825445
Bentler CFI = 0.8676589
SRMR = 0.09839428
AIC = 419.8332
BIC = -186.4002

called eutrophic factor correlated with DO, SD, $NO_2$, pH, describes 4.74% of variation.
2. The confirmatory factor analysis confirmed the structure described with the four latent variables. In discharge and pelagic zone *salinity*, *temperature*, *nitrogen, phosphorus*, in dam zone *salinity*, *temperature*, *nutrient* and *eutrophication*.
3. The correlations between the variables temperature and nitrogen, temperature and phosphorus or temperature – nutrient indicate to the vital importance of the air and water temperature in the transformations of the nitrogen and phosphorus compounds in the surface layer of the reservoir water. Water temperature is the result of seasonal changes and the discharge of heated waters from the power plant
4. The reservoir water salinity does not affect the remaining water quality factors, which was confirmed by lack of the correlation between the *salinity* variable and remaining latent variables. Possibly, the reservoir water salinity could be of an anthropogenic origin and could be caused by the wastewater discharge from the station of water treatment for technological purposes.

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