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Efficient Energy Management for the Smart Sustainable City Multifloor Manufacturing Clusters: A Formalization of the Water Supply System Operation Conditions Based on Monitoring Water Consumption Profiles

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Abstract: This study is devoted to improving the energy efficiency of urban infrastructure systems (UISs), in particular, the centralized water supply of a city multifloor manufacturing cluster (CMFMC), by developing the principles of effective energy consumption management. The CMFMCs are located in the residential area of a megapolis and include manufacturing and service enterprises, residential and non-residential buildings, and a city logistics node. Demand monitoring and identification of the influence of seasonal and social environmental factors on its fluctuations is considered as a tool for identifying changes in the operating conditions of the water supply system (WSS) for the CMFMC facilities. To identify the typical operating conditions of water supply facilities, an approach is proposed that involves the analysis of daily water consumption profiles (WCPs). The formation of a database, the formation of groups of the same type of daily WCPs, and the construction of typical daily WCPs for typical groups and their description are the main stages of the proposed approach. The database contains a set of classification characteristics that describe the daily water consumption and its unevenness, as well as the shape of the daily WCP. The principal component analysis was applied to determine the dominant components of daily water consumption. A set of morphometric parameters was used to describe the shape of the daily WCPs. The methods of cluster and discriminant analysis were used to identify the influence of seasonality and social factors on water consumption and to form groups of the same type of daily WCPs. The analysis of sets of similar type of daily WCPs for typical days of typical seasons was carried out for a formalized description of the typical operating conditions of water supply facilities. The results of the analysis are the clarification of the equations of the dominant components of daily water consumption, the determination of the average values of the characteristics of daily water consumption, and the construction and description of typical daily WCPs for typical operating conditions of water supply facilities. The research results were obtained on the basis of the data of the monitoring systems for water supply enterprises in Ukraine and Poland in 2021–2022. The obtained results are the basis for planning the water supply process and adjusting the operation modes of WSS pumping stations for the CMFMC, as well as planning power consumption for typical operating conditions, which will contribute to increasing the efficiency of water and electricity use.

Keywords: city multifloor manufacturing cluster; energy efficiency; demand monitoring; cluster analysis; discriminant analysis; water consumption profile; management

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1. Introduction

The current stage of society's development is characterized by the urbanization of territories. The development of large cities has led to the organization of city multifloor manufacturing clusters (CMFMCs) in their residential area, consisting of manufacturing and service enterprises, residential and non-residential buildings, and a city logistics node [1–3]. The activity of the CMFMCs aims at meeting the needs of citizens for goods and services of daily demand. In the context of growing urbanization [4], urban infrastructure systems (UISs) of such CMFMCs are an important link in human activity, welfare, and social and sustainable development of cities [5] and must meet the needs of users [6]. The UISs, such as energy infrastructure systems, centralized water supply and sanitation systems, and transport systems, provide the distribution of spatial services and are major consumers of fuel and energy (electricity, gas, etc.) and natural (water) resources. The growth of the population of cities and the growing demand for energy and natural resources requires the formation of an urbanized society based on the principles of sustainable development [7–9]. The sustainable development of the metropolis involves the design and planning of urban production processes of products and services, as well as the energy-efficient functioning of enterprises and logistics nodes to ensure the effective use of energy, water, and other natural resources to reduce climate change [1,2,10,11].

The EU strategy to achieve climate neutrality by 2050, formulated in the European Green Deal [12], and reduce greenhouse gas emissions by 55% by 2030 requires an appropriate contribution to the decarbonization of all sectors of the economy [13,14]. In order to implement the principles of sustainable development, the European Community has set itself the task of rationalizing final energy consumption, seeing in it a weighty alternative to building energy capacity. One of the principles of sustainable development designed to reduce greenhouse gas emissions is the principle of prioritizing energy efficiency in all production and technological processes [12]. According to the EU Directive (2018), the target for "improving energy efficiency is at least 32.5% of the 1990 level" [15]. This purpose is facilitated by the introduction of energy-efficient technologies to produce goods and services aimed at reducing energy consumption and CO_2 emissions [16,17]. Ensuring energy efficiency contributes to reducing the energy intensity of products and services within the CMFMC and aims to use resources efficiently without reducing the quality of life [17,18]. Therefore, energy-efficient production is a key factor for the sustainable development of cities, and efficient use of energy and natural resources is a priority for city manufacturing [11,19–21]. In this context, more and more attention is paid to the problems of improving energy efficiency and reducing final energy consumption. Ensuring the energy efficiency of urban production facilities requires effective management of technological processes and energy consumption, based on the analysis of information obtained from the monitoring system of their operation. In this regard, issues of development and improvement of the smart management system in city manufacturing are receiving increased attention [10,20–23].

The UISs operation of the CMFMC, such as electricity, heat, gas supply, centralized water supply and drainage systems, is influenced by climatic, territorial, and social factors, as well as the citizens' lifestyles [2,24]. The energy efficiency of UISs is determined by a set of internal technological and external factors that in a certain way affect the efficiency of their condition and functioning. Ensuring the efficient energy consumption of such UISs within the CMFMC requires taking into account the features and operating conditions of its facilities, the efficiency of the organization of the technological process, as well as the development of effective ways to identify hidden reserves for saving natural and energy resources [21,24]. The UISs are designed to meet consumer demand for a particular service, which is formed under the influence of various external factors. The changes in the demand for the services of UISs facilities determine the conditions of their operation. The efficiency of energy consumption in UISs depends on the effectiveness of solving tasks of planning, optimization, and management of the work of its objects, as well as planning and management of energy consumption taking into account cyclic changes of external factors that determine the conditions of system operation. Therefore, identifying the influence of social, climatic, and seasonal factors on the nature and irregularity of demand for UISs services and, in particular, water supply systems (WSSs) within CMUFCs, is an important step in effective planning of their operating conditions. Taking into account cyclical climatic, and seasonal changes when planning the consumption of energy resources for technological processes within WSS meets the requirements of the standards of the ISO 50000 series [25,26].

The purpose of this paper is to develop a mechanism for detecting regularities that determine the operation of WSS, which is based on the analysis of daily water consumption profiles (WCP) obtained from the monitoring system of the WSS functioning, as well as to formalize typical operating conditions of WSS facilities for effective planning of water supply and increasing the efficiency of water and electricity use.

The paper is organized as follows: Section 2 presents a literature review and some key points of the problem of energy efficiency of UISs, as well as centralized water supply systems within CMFMCs; Section 3 presents materials and methods of the proposed approach to formalize the conditions of WSS within CMFMCs; Section 4 presents the results of the implementation of the stages of the proposed approach to formalize the operating conditions of WSS facilities within CMFMCs, obtained on the basis of the data of the monitoring systems for water supply enterprises in Ukraine and Poland in 2021–2022; Section 5 is devoted to the discussion of the results and the final conclusions.

2. Literature Review

2.1. Energy Efficiency of Urban Infrastructure Systems and Monitoring of Their Operating Conditions

Ensuring the operation of UISs and improving energy efficiency and the use of natural resources (along with the introduction of modern technologies to improve the quality, efficiency, and effectiveness of technological processes) is based on the management of technological processes and energy consumption in accordance with the requirements of the standards of the ISO 50000 series [25,26]. One of the tools to ensure such management is the introduction of demand monitoring systems for services of the UISs within the CMFMCs. The issues of building monitoring data collection, transmission, and display systems in the dispatch control center, developing and improving methods for processing, systematizing, analyzing, and accounting of monitored information for planning the operation conditions and power consumption of UIS and its facilities, and for making management decisions are receiving increasing attention [27–36].

Planning of UISs operation conditions requires consideration of various input and output parameters and system constraints that determine the energy efficiency of their operation, considering the influence of the external environment. The technical characteristics of the UISs define the energy efficiency of its initial state and the ability to efficiently perform technological tasks. Technological parameters of the production process are the initial parameters for planning the conditions of the UISs operation and managing them in real time. External factors are random in nature and cause changes in the values of technological parameters and the actual operating conditions of the UISs and their facilities. Improving the energy efficiency of the UISs within the CMFMCs is related to the identification and consideration of important factors that affect the operating conditions in order to use them in the search for optimal management decisions [18]. An actual direction for improving the efficiency of the UISs operation is the development of systems for monitoring and managing its facilities in real-time [24,27,37–40]. The studies deal with the collection, transmission, and timely display of information on technological parameters of the UISs facilities in the control center [40,41], as well as with the development of principles for smart management of the operation conditions of the facilities, taking into account the monitoring data [27,29,31,34,37,41–43]. A lot of studies are devoted to the issues of planning and managing the operating conditions of UISs facilities, considering their energy efficiency [44–48]. Nevertheless, the issues of considering the influence of external factors on the technological parameters and operating conditions of the UISs objects are often overlooked. At the same time, the operation conditions of the UISs and their objects cannot be energy efficient, if its planning does not consider the actual needs of the technological process, which change depending on environmental conditions. The lack of information on typical conditions under which the UISs and its facilities can operate complicates the procedure for planning the operation conditions, considering their energy efficiency. In addition, the identification and formalized description of such conditions is the first step in the complex procedure for planning energy consumption and monitoring the energy efficiency of the UISs facilities [36,49,50].

Effective management of the UISs requires the introduction of comprehensive monitoring of the functioning of its facilities, considering the influence of the external environment to ensure prompt decision-making. The modern development of information technologies, technical means of automation, and computerization provide an opportunity to collect information on the actual conditions, parameters, and characteristics of the operating conditions of such UISs and their facilities. Examination of this information allows the identification of patterns needed to manage UISs to improve their energy efficiency [51–54].

Smart management of the UISs is based on various technologies for monitoring and analyzing the conditions of its operation. For example, in [46], such technologies are used to monitor and analyze the electrical load profiles of the UISs technological equipment to identify various levels of its load during a given time. The analysis of the electrical profiles of UISs facilities allows us to identify the operation conditions during a given time to make effective energy-efficient decisions [44,46–48].

One of the external factors that complicate the assessment of the energy efficiency of the UISs operation is the stochastic demand of consumers for its services, which is considered a systemic disturbance in the observed time interval [55]. Therefore, taking into account the demand of certain groups of consumers for the services of the UIS in specified time intervals is the basis for energy efficiency management [27].

The main indicator of the operating conditions of the UISs is the daily demand profile for their services. Thus, to ensure the effective operation of the UISs, including the rational use of resources, it is necessary to plan the operating conditions of their facilities, considering the daily profile of demand for their services [56]. Social (reflecting the way of life: type of day—working, weekend; time of day) [57], climatic and seasonal factors affect the periodic fluctuations (seasonal, weekly, daily) and the dynamics of consumer demand for services of the UISs [51,55,58,59]. Therefore, cyclical changes in consumer demand should be taken into account for determining the actual operating conditions of the UISs. The formalization of the typical operating conditions of the UIS and its objects, taking into account the data of the demand monitoring system, is a component of the procedure for planning the technological process, the operation of the UIS objects, and controlling the energy efficiency of the UIS.

2.2. Aspects of the Energy-Efficient Operation of the Water Supply System

The centralized water supply and sanitation systems are among the most important UISs necessary for the life support of a megapolis. The operating conditions of the megapolis WSS are formed under the influence of many factors that depend on the reserves and quality of natural waters, the technical parameters of the WSS, and the way of life of people. The WSS should provide the population of the megapolis with drinking water that meets quality standards, under-regulated pressure, and in the required quantities [5,60,61]. The optimal balance between consumer demand and water supply, which excludes water shortage and ensures a reliable water supply for social and production purposes, is the main guarantee for the vital activity and functioning of the CMFMCs of the metropolis.

The modern WSS contains a number of subsystems that provide the pumping of raw water, preparation, supply to the network, and transportation of water to consumers and are characterized by a complex relationship between technology and the process of energy consumption [62]. The main energy resource that ensures the WSS operation is electrical energy. Technological facilities of the WSS consume a large amount of electricity at each stage of the water supply process [5,63,64]. According to the EU Directive (2018), electricity consumption in the water supply and sanitation sector accounts for 3.5% of electricity consumption in the EU [15]. In addition, the WSS is a consumer of a vital natural resource-water, the reserves of which are limited in the required quality. At the same time, water losses in water supply networks are significant (e.g., in the EU they account for 24% of the total amount of water consumed [15]). Improving the efficiency of water and electricity consumption in the megapolis WSS under water scarcity and climate change problems is a priority task for water supply companies [6,62,65,66].

As a consumer of electricity, the WSS is characterized by a complex interconnection between internal subsystems. The total power consumption in the WSS includes the power consumption related to the operation of pumping units of the first and second lift stations, booster pumping of the third lift station, technological installations of water treatment, and general plant needs of the enterprise. The features of the water supply process, in particular, the use of water as a product and as a natural resource, not only determine the efficiency of electricity use in individual structural elements but also affect the efficiency of energy resource use in the WSS as a whole. The pumping stations subsystem, which ensures water pumping, is the largest consumer of electrical energy among the subsystems involved in the water supply process [5,60,63–68]. The electricity consumption for pumping water depends on the volume of pumped water and the generated head (pressure). The operating modes of pumping stations depend on changes in the conditions of water consumption (volume and daily fluctuations of water consumption) [63]. Water consumption is uneven over the course of the day [57,69], as well as over the course of the week, month, and year, and arises under the influence of many independent factors: seasonal, climatic (precipitation, air temperature) [59], social (working hours of companies and organizations of the CMFMCs, weekdays, weekends, governmental and religious holidays). Effective planning and optimization of the operating mode of pumping stations improve the efficiency of energy consumption [61,68,70].

However, the planning of the water supply without taking into account the demand leads to errors in planning the operation of pumping stations, the occurrence of overpressure, which contributes to an increase in water losses due to leaks in the water supply network, which in turn leads to an increase in electricity consumption [5], which is one of the causes of the inefficient operation of the WSS. Therefore, the task of subsystem operation management to ensure energy-efficient operating conditions of the WSS is an important component to save energy and water resources. At the same time, it is necessary to take into account daily fluctuations of water consumption in the megapolis CMFMCs [61].

Ensuring efficient water supply to the network requires pre-planning the operation mode of pumping stations (number of pumps in operation, their combinations, operating time, and sequence of switching on and off) and developing a control strategy for a given period of time (usually 24 h) to maintain the required pressure in the water supply network and to ensure the emergency status in the clean water reservoirs and the possibility of its restoration [5,6,68–71]. Therefore, the daily WCPs, set taking into account the cyclic variations in water demand, are the basis for effective planning of pump operation schedules and the water supply process, as well as for adjusting pump operation schedules taking into account changes in consumer demand [72]. Usually, the total daily water consumption amount and its average and maximum values during the day are used as characteristics of water demand [5]. However, the cyclic changes in water consumption are accompanied by changes in daily WCPs and shifts in their maximum values, which complicates the process of water supply planning [57]. Moreover, the process of water supply to consumers is characterized by great inertia. Therefore, in order to plan the operation of water supply facilities, it is necessary to determine the management strategy in advance, considering water demand [27]. Under these conditions, one of the approaches to ensure effective water supply planning and adjust pumping operation schedules is to create a database of daily

WCPs and analyze them to look for hidden regularities that determine the formation of water supply conditions [53,54,72].

3. Materials and Methods

The task of formalizing conditions of WSS facilities operation is considered as a task of recognizing changes in water demand considering information on its daily WCPs. The solution of this task requires the preliminary revealing of hidden regularities in water consumption formation and their formalized description. For this purpose, the information on daily WCPs obtained from the monitoring system should be processed and arranged in a certain way. This requires the implementation of successive stages of data analysis to extract new knowledge from the DB of daily WCPs. As an object of study, the pumping station of the second lift was chosen, operating for the WSS distribution network.

3.1. Formation of the Feature Space for Describing the Daily Water Consumption Profile

Improving the information content of the results of monitoring changes in the consumer demand for water supplies requires the formation of the information feature space for describing the daily WCPs.

Let each daily WCP be a realization $z_j(t_i)$ of a random process of water consumption $Z(t)$, $t \in T$ in the annual observation interval T, $t \in [1;8760]$; $j \in [1;365]$; $i \in [1;n]$, $n = 24$.

3.1.1. Formalization of the Contribution of Hourly Values of Water Consumption to the Configuration of the Daily Profile

The planning of the water supply process is preceded by the determination of the total stepwise water consumption chart, which has several multi-hour levels, within which there is a slight fluctuation in the hourly values of water consumption. This chart is the basis for optimization of the conditions of water supply to the network, which is limited to the choice of the timing of switching on and off the pumps. Therefore, it is necessary to highlight the dominant components of the daily WCPs, which will correspond to the stepwise chart of the water supply. It is expected that the hourly values of water consumption within a day, which are closely correlated with each other, should also be closely correlated with a certain factor. Therefore, the mathematical apparatus chosen for daily WCPs analysis was the principal component method (PCA), which can reveal sufficient hidden factors [73] and does not require prior selection of groups of input values. PCA provides the detection n of s components that explain the total variance and correlation of the m original random variables.

3.1.2. Description of Daily Water Consumption Irregularity and Shape of Its Profile

To describe daily WCPs, it is necessary to take into account the parameters reflecting the total volume of daily water consumption (Table A1), its average, maximum, and minimum values during the observation period, and the characteristic of irregularity of its profile: dispersion and standard deviation, shape factor, maximum factor, filling factor, and irregularity factor [74].

The daily WCPs are characterized by a different form for different days of the week. To describe the shape of the daily WCPs, a morphometric approach was used as one of the tools for analyzing figures of various shapes. The daily WCPs are preliminarily converted into a polygon of a certain shape in the radar chart (RC) (Figure A1). The distance from the center of the coordinates to the top of the polygon corresponds to the value of water consumption at a given time. The shape of the RC was described by a set of morphometric parameters (Table A1) [75,76].

3.1.3. Formation of Feature Information Space for Daily Water Consumption Profile

The description of the daily WCPs is implemented in the following three blocks (Table 1): (a) daily water consumption description block, contains the values of daily water consumption and its constituent components (the value of water consumption in different periods of the day); (b) daily water consumption irregularity description block, contains the values of absolute characteristics of daily water consumption irregularity; (c) daily WCP from description block, contains morphometric parameters, which are defined based on preliminary presentation the daily WCPs as their RCs.

Table 1. Description of the daily WCPs and their irregularity.

Daily Wcps Form	Stepwise Chart			Radar Chart
Name block	Daily water consumption description block	Daily water consumption irregularity description block		Daily WCPs form description block
Type of description	Daily water consumption and its constituent components	Daily water consumption absolute irregularity indicators	Daily WCPs irregularity indicators	Daily WCPs morphometric parameters
Parameters of description	Z, Z_s	Z_{max}, Z_{min}, Z_{ms}, Z_m	σ^2, σ, K_{forms}, K_{max}, K_{fill}, K_{irreg}	P, S, (x_c, y_c), M_1, M_2, M_3, M_4, R_{max}, R_{min}, L_1, L_2, S_2, α_{L1}

The characteristics of daily water consumption and its irregularity for a given type of day in a given season form a feature information space for revealing hidden regularities in water consumption, taking into account the influence of external factors.

3.2. Formalization of Hidden Regularities in Water Consumption

The task is to determine the groups of daily WCPs that are most similar to each other according to certain criteria. To solve this task, the mathematical apparatus of pattern recognition is used. Due to the lack of information about possible classes, the "without teacher" pattern recognition procedure (automatic classification) is used to form a training sample, and then the classification results are refined using the "with teacher" pattern recognition procedure. Thus, the classification procedure is two-stage and is based on the use of standard procedures of cluster analysis (CA) and discriminant analysis (DA).

Step 1—automatic classification "without teacher"; classifier type—CA method.

Each daily WCP z_j from the set Z is described by the feature system m and is represented by a point in the linear feature space: $z_j \in X^m$. As an assumption, we assume that all indicators m of the feature space are significant and have the same weight. At the initial stage, a hierarchical agglomerative CA method is applied [77,78]. Since the hierarchical CA method sequentially groups the objects of classification and does not provide for determining the optimal number of classes obtained, the hierarchical CA method is used for preliminary determination of the number of classes and for forming a hypothesis about the probable belonging of an object to a certain class. Then an iterative reference type method is applied, in particular, the k-means method based on the minimization of intracluster variance [77]. Its use contributes to the formation of daily WCP typical groups and to the acquisition of a training sample for the formation of rules for the identification of daily WCPs belonging to one of the typical classes.

Step 2—automatic classification "with teacher"; classifier type—DA method.

The DA method is used to classify daily WCPs based on learning [77]. Together with the classification features, the training sample contains a grouping variable that determines whether daily WCPs belong to a certain class, the value of which is determined for each daily WCP at the first step. Optimization of the set of initial features $X_1, \ldots, X_m$ is performed using a step-by-step procedure. The result is the formation of a set of discriminant variables that best divide objects into groups. The classification discriminant functions constructed for each class, taking into account the generated set of discriminant variables, are used as a crucial rule to determine whether daily WCPs belong to a particular class.

Thus, the use of the CA method ensures the detection of hidden regularities in the water consumption formation. The use of the method DA allows the construction of classification discriminant functions to determine whether the daily WCP belongs to one of the typical classes and the formation of groups of similar types of graphs.

3.3. Formalized Description of Typical Operating Conditions for Water Supply Facilities

The formation of groups of daily WCPs provides the possibility to sample retrospective data necessary for a formalized description of changes in water consumption, taking into account the influence of seasonal and social factors. Such a description allows us to determine the average values of the characteristics of daily water consumption (the value of daily water consumption and its components) and the limits of their change for each of the formed classes. A selective mathematical expectation of its values, formed by objects of a certain class, is used as the average value of any characteristic of water consumption. The interval estimate of the sample mathematical expectation (confidence interval) is used as an allowable limit for the change of the characteristics of water consumption.

The actual daily WCP is the range of values in the *Z-t* coordinate field, limited by the maximum and minimum water demand curves. Analysis of daily WCPs of a similar nature provides the opportunity to form the average daily WCPs for the identified typical classes. The procedure of determining the average daily water consumption and the limits of its change is applied to the obtained sets of hourly water consumption values. The result of its application is to obtain the average values of water consumption and the limits of its change for each hour of the day, which were used to create a typical daily WCP for each typical day of each season. Typical daily WCP corresponds to the average expected daily water consumption, and the limits of its change correspond to the minimum and maximum expected daily water consumption. The resulting typical daily WCPs are the basis for planning water supply conditions and efficient operation of WSS facilities, and power consumption.

The following section presents the results of the implementation of the stages of the proposed approach to formalize the operating conditions of WSS facilities within CMFMCs, obtained on the basis of the data of the monitoring systems for water supply enterprises in Ukraine and Poland in 2021–2022.

4. Results

4.1. Study of Water Consumption Regularities Based on Daily WCPs Analysis

Water consumption has an irregular character during the day (which is determined by sociological conditions). A preliminary analysis of daily water consumption has shown that one of its components is a daily cycle. The temporal variation of water consumption reflects the cyclicity of daily life: working hours, and resting hours. Water consumption is almost the same at the beginning of the day and has a scatter of values during the daytime. Water consumption is almost the same at the beginning of the day and has a scatter of values during the daytime. The daily cycle contains clearly defined periods of main water supply (daytime), background water supply periods (nighttime), and transitional periods. Significant differences in daily WCPs usually occur only during the day. Daily WCPs also differ from each other depending on the time of year and the type of day of the week.

Daily WCPs change throughout the year due to the seasonality of water consumption. In addition to daily cyclicity, intra-week cyclicity and annual frequency of daily WCP are also observed. The social factor, especially governmental and religious holidays, has a great influence on the form of the daily WCPs. In addition, daily WCPs on some days may deviate from the general trend. One of the reasons for this deviation can be, for example, accidents in the CMFMC water supply network.

4.2. Determining the Contribution of Hourly Water Consumption Values to the Daily Profile Configuration

The result of applying the factor analysis of the daily WCPs obtained from the water consumption monitoring database is the determination of the principal component equations.

The rotation of the factor space by the “quartimax” method was performed to improve the interpretation of the principal components. The results of the application of the principal component analysis are presented using a matrix of factor loadings (Table 2). The formed three main components describe 94.3% of the total variance.

Table 2. Matrix of factor loadings of the principal components.

Indicator	Component		
	F_1	F_2	F_3
1	0.254	0.354	0.911
2	0.137	−0.281	−0.922
3	0.206	−0.245	−0.913
4	0.234	−0.181	−0.951
5	0.009	−0.192	−0.914
6	0.326	0.476	0.822
7	0.271	0.717	−0.318
8	0.958	−0.242	−0.128
9	−0.948	−0.188	−0.172
10	−0.964	−0.142	0.235
11	−0.968	−0.121	0.184
12	−0.973	0.102	−0.181
13	−0.969	−0.115	0.212
14	−0.932	−0.201	0.268
15	−0.917	−0.171	0.272
16	−0.913	0.148	0.175
17	−0.922	−0.062	0.082
18	0.958	0.231	−0.135
19	−0.948	0.341	0.045
20	−0.933	−0.161	−0.354
21	0.891	0.418	0.121
22	0.379	0.725	−0.118
23	0.504	0.708	0.432
24	0.373	0.719	0.418
Eigenvalues of the factors, λ_j	4.738	2.127	1.063
Weight of factors, %	61.5	21.5	11.3

The analysis of factor loadings allows us to determine the values of hourly water consumption, which are dominant in each component.

The first principal component F1 (61.5% of the total variance) includes the value of daily water consumption from 8 a.m. to 9 p.m. These values form the main water consumption during the daytime. The second principal component F2 (21.5% of the total variance) includes the values of daily water consumption at 7 a.m. and from 10 p.m. to 12 a.m. These values form water consumption in the morning and in the evening hours of the day. The third principal component F3 (11.2% of the total variance) includes the value of daily water consumption from 1 a.m. to 6 a.m. These values form the water consumption during the night period of the day. Therefore, component F1 corresponds to water consumption during the daytime; component F2 characterizes intermediate values of water consumption during the morning and evening periods; component F3 corresponds to water consumption during the night.

The values of hourly water consumption, which are dominant in the determination of each main component, should be considered as forming the corresponding components of water consumption during the day. It allows us to form equations of the dominant components of daily water consumption for a reasonable determination of water consumption volumes in different periods of the day (Table 3).

Table 3. Dominant components of daily water consumption.

Interpretation of Dominant Component	Equation of Components of Daily WCP
Water consumption in the day time	$Z_1 = \sum_{i=8}^{21} z(t_i)$
Water consumption in the interim period of day	$Z_2 = \sum_{i=(7,22,23,24)} z(t_i)$
Water consumption in the night time of day	$Z_3 = \sum_{i=1}^{6} z(t_i)$

4.3. Formation of Groups of the Same Type of Daily Water Consumption Profiles and Interpretation of Classification Results

The formation of groups of the same type of daily WCP is based on the following steps:

1. The sets formation of classification features.

Since the simultaneous consideration of many features that describe the daily WCP makes it difficult to interpret the results obtained, their grouping was carried out in two stages: Stage 1—according to the influence of seasonality; Stage 2—according to the influence of social factors (type of day) considering the results of the first stage.

The analysis of the annual schedule of daily water consumption indicates fluctuations in water consumption depending on the season of the year and time of day. The characteristics of blocks 1 and 2 form an information feature space for identifying the impact of seasonal factors on water consumption. The set of classification variables also contains absolute characteristics of uneven water consumption during the daytime. Therefore, the description of the daily WCP is performed using the following classification features: Z, Z_1, Z_2, Z_3, Z_{max}, Z_{min}, $Z_{min,d}$, Z_m, $Z_{m,d}$, σ^2, σ_d^2. As a result, a matrix of observations was formed to identify the influence of seasonality (Table 4).

Table 4. A fragment of the observation matrix to detect the effect of seasonality.

Indicator	Date			
	1 September 2021	2 September 2021	3 September 2021	4 September 2021
Z	56,129	57,114	57,722	57,189
Z_1	42,503	43,408	43,104	43,088
Z_2	10,570	11,048	11,556	11,275
Z_3	3056	2658	3062	2826
Z_{max}	3396	3670	3501	3411
Z_{min}	500	425	500	170
Z_m	2338.7	2379.7	2405.1	2382.7
$Z_{m,d}$	2530.9	2425.1	2551.5	2452.3
σ^2	1,211,794	1,388,683	1,280,929	1,304,360
σ_d^2	32,282.8	91,946.5	3960.3	33,774.5

The change in the way of life of the population on weekends, holidays, and workdays leads to a change in the form of daily WCPs. Therefore, in order to identify the similarity in daily WCP, one must consider its shape. Consequently, the characteristics of block 3 form an information feature space for identifying the influence of social factors on water consumption. The following morphometric indicators were used to describe the daily WCP form: P, S, R_{min}, R_{max}, M_1, M_2, M_3, L_1, L_2, α_{L1}, M_4, S_{conv}, P_{conv}, M_{2conv}, d. As a result, a matrix of observations was formed to identify the influence of social factors (Table 5).

Table 5. A fragment of the observation matrix for identifying the influence of social factors.

Morphometric Parameters	Date			
	1 September 2021	2 September 2021	3 September 2021	4 September 2021
P	812.2	816.65	867.38	778.87
S	34,157	33,948	36,974	35,447
R_{min}	50.33	41.87	52.89	69.86
R_{max}	142.44	135.37	147.51	131.05
L_1	263.81	265.31	286.57	249.58
L_2	143	132.01	143.28	158.35
M_1	0.35	0.31	0.36	0.53
M_2	0.65	0.64	0.62	0.73
M_3	0.54	0.5	0.5	0.63
M_4	0.86	0.84	0.85	0.92
P_{conv}	736.72	739.68	777.72	723.68
S_{conv}	38,962	39,453	42,955	37,943
M_{2conv}	0.9	0.91	0.89	0.91
α_{L1}	143	130	139	154
d	147.14	163.34	155.05	156.97

2. The sets formation of informative classification features.

An important condition for the reliability of the results is the "orthogonality" of the data, which implies that there should not be high correlation values between the features. In the preliminary stage, an analysis of the degree of correlation between the features was performed [79]. The selection of informative classification features was carried out by sequential exclusion of interrelated features from the initial set. The correlation coefficients were tested for significance using the Fisher-Yates test to establish a valid relationship between the features and to detect multicolinearity. As a result, the significant classification variables were accepted in stage 1: Z, Z_{max}, Z_{min}, $Z_{min,d}$, σ_d^2; at stage 2: S, M_1, M_2, M_3, α_{L1}, M_4, d.

3. Determining the number of classes.

The result of object grouping by the hierarchical CA method depends on the choice of the optimality criterion (proximity measure) and the union strategy (determining the distance between groups). Based on the analysis of various metrics and strategies, and based on the meaningfulness of the interpretation of the results, the Euclidean distance was chosen as the similarity measure and the full connection strategy as the union strategy. The result of the procedure of the hierarchical CA method is a dendrogram whose visual analysis allowed us to determine the number of classes and the interpretation of the results.

The analysis of the dendrogram has shown that for the identification of the effect of seasonality on water consumption, the number of classes can be equal to five: Class 1—contains the daily WCPs corresponding to the period of preventive maintenance in the hot water supply system; Class 2—contains daily WCPs corresponding to the period of the heating season, that is, winter season; Class 3—contains daily WCPs corresponding to the period of spring–summer–autumn; Class 4—contains daily WCPs of different months and seasons, that is, uncharacteristic days; Class 5—contains the daily WCPs corresponding to the first of January. Dividing of daily WCPs into groups by type of day at the second stage is performed for each typical season, taking into account the results of the division at the first stage. Based on the analysis of the dendrograms obtained for Class 1 and Class 3, the number of classes was taken to be equal to three: Class 1—contains daily WCPs corresponding to working days; Class 2—contains daily WCPs corresponding to weekends and holidays; Class 3—contains daily WCPs of different types of days, that is, uncharacteristic days. The analysis of the dendrogram showed that the number of classes can be four in order to determine the influence of social factors: Class 1—contains the daily WCPs corresponding to working days; Class 2—contains the daily WCPs corresponding to weekends and holidays; Class 3—contains the daily WCPs of different types of days, that is, uncharacteristic days; Class 4—contains the daily WCPs corresponding to the first of January. The allocation of the first of January to a separate class in the two stages of the daily WCPs classification emphasizes the importance of the influence of social factors on water consumption.

4. Dividing of daily WCPs into groups of the same type and forming a training sample.

The k-means method was applied to partition daily WCPs into groups of a similar type. The hierarchical analysis revealed a class that contained only a single daily WCP corresponding to January 1, and, therefore, this daily WCP was excluded from further consideration.

The number of classes is assumed to be four for the first stage and three for the second. The unweighted Euclidean distance is used as a measure of the distance between the parameter vector and the class centroid. The result of performing the k-means CA procedure is to determine whether each daily WCP belongs to a particular class. Calculations of the mean values of the features of each class, within-group variation for each of the features, Euclidean distance between classes, as well as analysis of variance and F-test were performed to verify the correctness of clustering of daily WCPs and to test the significance of the classes selected. Analysis of the obtained results of the division of daily WCPs into clusters revealed cases of classification of daily WCPs that were not consistent with the accepted interpretation. In this regard, the sample of clustering objects was corrected by excluding such profiles from consideration. The results of the analysis of variance also revealed that the variable Z_{min}, defined as an informative classification variable to identify the influence of seasonality, as well as variables M_2 and d, defined as informative classification variables to identify the influence of social factors, have a significance level $p > 0.05$ (their influence on the classification is insignificant). Therefore, these variables were excluded from the classification.

The results of checking the correctness of clustering of daily WCPs and testing the results of clustering (Table 6) confirmed the validity of partitioning the set of observations into the pre-selected number of classes, the correctness of their construction procedures, the reliability of the classes selected, as well as the homogeneity of classification features of daily WCPs combined into one class and the significance of their contribution to the distribution of daily WCPs into groups. The results of the analysis of variance showed that in the sample of variables, the highest values of F-test indicators were characterized by Z (daily WCPs, stage 1) and M_3 (elongation, stage 2). It should be noted that the data on the averages for each variable are consistent with the F-test values. The value of the significance level for all classification attributes is significantly less than 0.05, indicating that the influence of these attributes is significant. The use of the k-means method made it possible to form typical groups of daily WCPs, which formed the training sample.

4.4. Interpretation of Discriminant Results and Construction of Object Classification Rules

The obtained results of partitioning the daily WCPs using the k-means method were used to refine the partitioning results and form rules for identifying their belonging to one of the typical classes using the DA method.

1. Verification of the statistical significance of discrimination and the correctness of training samples.

A step-by-step DA algorithm was applied to eliminate subjectivity when choosing discriminant variables that have the greatest impact on distinguishing classes. The F-test is applied at each step to determine whether a variable can separate classes. After the selection of informative discriminant variables, the correctness of the training samples was checked. The sample Mahalanobis distance from the point of observation to the center of the desired class in the multidimensional space of discriminant variables was used as the degree of difference belonging to the class of some observation. The correctness verification of the a priori distribution of objects into classes was performed using the classification matrix. Obtaining correct training samples from the original training samples was performed by excluding the objects which, based on their indicators, do not correspond to the majority of objects forming the homogeneous group. The displacement of the gravity centers of the group (average vector) was considered when removing objects from the group. As a result of the exclusion of atypical observations, the overall coefficient of correctness of the training samples was 100%. The results of checking the correctness of the training sample are demonstrated in the example of identifying the influence of social factors for the third Class by season (Table 7).

Table 6. Fragment of checking clustering results.

Analysis Stage	Analysis Stage Results				
Identification of the influence of seasonality					
Standardized means of the class variable	Var.	Class number No. 1	No. 2	No. 3	No. 4
	Z	0.41	−0.87	0.71	−1.84
	Z_{max}	0.95	−0.97	0.21	−0.53
	$Z_{min,d}$	−0.41	−0.11	0.77	−2.32
	σ_d^2	1.1	−0.68	−0.38	1.1
Euclidean distances between classes (distances below diagonal, squared distances above diagonal)	Class number	No. 1	No. 2	No. 3	No. 4
	No. 1	0.000	5.11	1.17	1.46
	No. 2	2.26	0.000	1.21	2.79
	No. 3	1.08	1.1	0.000	6.4
	No. 4	1.21	1.67	2.53	0.000
Analysis of variance	Var.	Between SS	Within SS	F-criterion	p-level
	Z	231.46	132.11	188.14	0.0000
	Z_{max}	211.85	145.19	169.91	0.0000
	$Z_{min,d}$	210.50	156.4	160.18	0.0000
	σ_d^2	218.50	137.72	174.64	0.0000
Identification of the influence of social factors (on class 3rd by season)					
Standardized means of the class variable		Var.	Class number No. 1	No. 2	No. 3
		S	0.46	−0.79	0.03
		M_1	0.35	−0.81	0.34
		M_3	−0.02	−0.72	1.77
		α_{L1}	0.26	0.08	−1.74
		M_4	0.53	−0.71	−0.53
Euclidean distances between classes (distances below diagonal, squared distances above diagonal)		Class number	No. 1	No. 2	No. 3
		No. 1	0.00	0.99	1.72
		No. 2	0.99	0.00	2.49
		No. 3	1.30	1.59	0.00
Analysis of variance	Var.	Between SS	Within SS	F-criterion	p-level
	S	119.70	59.01	43.98	0.0000
	M_1	97.92	51.89	48.02	0.0000
	M_3	107.92	67.04	140.97	0.0000
	α_{L1}	94.31	85.64	81.04	0.0000
	M_4	101.41	63.99	57.01	0.0000

Table 7. A fragment of the results of checking the correctness of training samples (the identification of the influence of social factors on class 3rd by season).

	Percent Correct	**G_1:1**	**G_2:2**	**G_3:3**
		p **= 0.56**	p **= 0.32**	p **= 0.12**
G_1:1	100	98	0	0
G_2:2	100	0	54	0
G_3:3	100	0	0	20
Total	100	98	54	20

The generalized results of the DA method (Table 8) confirmed the statistical significance of discrimination, the significance and information content of the classification variables selected at the stage of automatic classification, as well as the conclusions about the insignificance of the Z_{min} feature for stage 1 and the features M_2 and d for stage 2. The total value of Wilks' statistics considering all variables, approaches zero, which indicates a good quality of training sample discrimination. The F-test demonstrates the differences between the mean values of the variables for the selected groups. The significance of the F-test confirms the significant differences between groups of daily WCPs. The F-test value for each variable confirms its statistical significance in discrimination and the significance of its contribution to predicting daily WCPs' group membership. The values of tolerance and the coefficient of multiple correlations for each variable indicate that the variables do not have redundancy properties. Variables Z for stage 1 and M_3 for stage 2 have the greatest contribution in terms of group discrimination.

Table 8. Fragment of DA results.

Analysis Stage	**Analysis Stage Results**						
Identification of the influence of seasonality	Discriminant function analysis summary; Step 4 (Final step), Number of variables in the model: 4; Grouping: Class (four grps.) Wilks' Lambda: 0.12681 approx. F (12.49) = 91,1 $p < 0.0000$						
		Wilks' Lambda	Partial Lambda	F-remove (2.165)	p-level	Tolerance	1-Tolerance (R^2)
	Z	0.17	0.805	30.38	0.000000	0.96	0.04
	Z_{max}	0.151	0.882	17.61	0.000000	0.681	0.319
	$Z_{min,d}$	0.139	0.911	10.77	0.000000	0.561	0.439
	σ_d^2	0.141	0.958	5.71	0.000001	0.481	0.519
Identification of the influence of social factors (on class 3rd by season)	Discriminant function analysis summary; Step 5 (Final step), Number of variables in the model: 5; Grouping: Class (three grps.) Wilks' Lambda: 0.10134 approx. F (10.33) = 70.663 $p < 0.0000$						
		Wilks' Lambda	Partial Lambda	F-remove (2.165)	p-level	Tolerance	1-Tolerance (R^2)
	M_3	0.21	0.52	78.75	0.000000	0.97	0.03
	α_{L1}	0.15	0.72	32.89	0.000000	0.93	0.07
	S	0.13	0.79	21.93	0.000000	0.92	0.08
	M_4	0.12	0.85	15.08	0.000001	0.91	0.09
	M_1	0.11	0.89	10.85	0.000040	0.86	0.14

2. The construction of discrimination functions.

The canonical analysis of the discriminant model (Table 6) was carried out to determine the nature of discrimination. The analysis of canonical discriminant functions (DF), the so-called canonical roots, is performed to estimate the level of canonical correlation. The number of canonical roots that best reflect the differences between groups of daily WCPs is determined by considering the number of classes for each stage. The canonical model is a model with three canonical roots for stage 1 and two canonical roots for stage 2. The unstandardized coefficients of canonical variables were used to construct canonical discriminant functions (DF), calculate the value of DF, and determine the weight of DF in grouping daily WCPs. The results of the evaluation of the effect of removing the canonical roots showed a close relationship between DF and groups of daily WCPs, the effectiveness of the participation of variables in distinguishing between groups, as well as the significance of DF, that is, good discrimination of groups of daily WCPs. The standardized coefficients of the canonical variables were used to interpret the direction and contribution of the variables to the DF value. The eigenvalue and cumulative proportion of explained variance are calculated for each DF. The factor structure matrix, which reflects the correlation of variables and discrimination functions, is used to explain the content of DF. The analysis of the mean values of the canonical variables was performed to determine the nature of discrimination for each DF. This allowed the identification of groups of daily WCPs most likely to be identified by a particular DF. The results of the canonical analysis are demonstrated on the example of identifying the influence of social factors for the third Class by season (Table 9).

Table 9. A fragment of the results of the canonical analysis (the identification of the influence of social factors on class 3rd by season).

Analysis Stage	**Analysis Stage Results**						
Non-standardized coefficients for canonical variables	Variable			Root 1			Root 2
	M_3			−1.591			0.049
	M_4			−0.169			−0.669
	α_{L1}			0.819			−0.321
	S			0.189			−0.749
	M_1			0.219			−0.631
	Constant			−0.051			−0.014
	Eigenvalue			3.071			1.425
	Cum. prop.			0.679			1.000
Equation of canonical discriminant functions	$d_1 = -0.051 - 1.519 \cdot M_3 - 0.169 \cdot M_4 + 0.819 \cdot \alpha_{L1} + 0.189 \cdot S + 0.219 \cdot M_1$; $d_1 = -0.014 + 0.04 \cdot M_3 - 0.669 \cdot M_4 - 0.321 \cdot \alpha_{L1} - 0.749 \cdot S - 0.631 \cdot M_1$.						
Chi-Square test s with Successive Roods Removed	Roots removed	Eigenvalue	Canonical R	Wilks' Lambda	Chi-Sqr	df	*p*-level
	0	3.07	0.87	0.11	379.78	10	0.000
	1	1.43	0.77	0.42	148.01	4	0.000
Standardized coefficients for canonical variables	Variable			Root 1			Root 2
	M_3			−0.941			0.031
	M_4			−0.141			−0.509
	α_{L1}			0.541			−0.31
	S			0.149			−0.611
	M_1			0.166			−0.471
	Eigenvalue			3.77			1.431
	Cum. prop.			0.683			1.000
Discriminant Function Analisis Results	DF			Eigenvalue			% variance explained
	d_1			3.07			68.32
	d_2			1.43			31.69
	DF			Eigenvalue			% variance explained
	d_1			3.07			68.32
	d_2			1.43			31.69
	DF			Eigenvalue			% variance explained
Factor structure matrix	Variable			Root 1			Root 2
	M_3			−0.791			−0.231
	M_4			0.019			−0.652
	α_{L1}			0.541			−0.199
	S			−0.079			−0.631
	M_1			−0.231			−0.539
Means of canonical variables				Root 1			Root 2
	G_1:1			0.281			−1.025
	G_2:2			1.199			1.522
	G_3:3			−4.651			0.779

The results of the canonical analysis showed good discrimination between groups of daily WCPs, a close relationship between DF and groups, the effectiveness of the participation of the selected discriminant variables in distinguishing between groups, and also confirmed the need to combine the obtained DF to distribute daily WCPs among classes and interpret the classification results. The analysis of the significance of DF and the weight of the discriminant variables showed that the variable Z was the most important in the daily WCPs discrimination model for stage 1 (although the variables $Z_{min,d}$ and Z_{max} are also important). This confirms the assumption that there are differences in daily WCPs due to changes in the nature of water consumption at different times of the year. Variables M_3 and α_{L1} are the most important for stage 2. This confirms the assumption that there are differences in the daily WCPs due to the change in the rhythm of life on workdays and weekends.

3. Formation of functions for the classification of new objects.

In the final stage of DA, the classification functions by season and day type were created for each season. The coefficients of the classification functions were used to make up the corresponding equations (Table 10), which provide the possibility of predicting whether an object belongs to one of the typical classes.

Table 10. A fragment of the results of compiling classification functions.

Analysis Stage	**Analysis Stage Results**				
Identification of the influence of seasonality					
Coefficients of classification functions	Variable	G_1:1 p = 0.022	G_2:2 p = 0.354	G_3:3 p = 0.389	G_4:4 p = 0.264
	Z	1.555	3.173	2.939	0.521
	σ_d^2	3.251	0.111	0.961	0.763
	$Z_{min,d}$	−6.431	0.919	1.091	1.852
	Z_{max}	0.559	1.609	0.118	2.141
	Constant	1.139	3.301	2.652	3.461
Equations of classification functions	$h_{S1} = 1.139 + 1.555 \cdot Z + 0.559 \cdot Z_{max} - 6.431 \cdot Z_{min,d} + 3.251 \cdot \sigma_d^2$; $h_{S2} = 3.301 + 3.173 \cdot Z + 1.609 \cdot Z_{max} + 0.919 \cdot Z_{min,d} + 0.111 \cdot \sigma_d^2$; $h_{S3} = 2.652 + 2.939 \cdot Z + 0.118 \cdot Z_{max} + 1.091 \cdot Z_{min,d} + 0.961 \cdot \sigma_d^2$; $h_{S4} = 3.461 + 0.521 \cdot Z + 2.141 \cdot Z_{max} + 1.852 \cdot Z_{min,d} + 0.763 \cdot \sigma_d^2$.				
Identification of the influence of social factors (on class 3rd by season)					
Coefficients of classification functions	Variable	G_1:1 p = 0.573	G_2:2 p = 0.321	G_3:3 p = 0.118	
	M_3	0.579	1.952	5.41	
	M_4	0.682	1.121	0.311	
	α_{L1}	0.583	0.522	−3.988	
	S	0.781	0.961	−1.531	
	M_1	0.712	0.679	−1.532	
	Constant	1.142	3.111	1.312	
Equations of classification functions	$h_{D1} = 1.142 + 0.781 \cdot S + 0.712 \cdot M_1 + 0.579 \cdot M_3 + 0.583 \cdot \alpha_{L1} + 0.682 \cdot M_4$; $h_{D2} = 3.111 + 0.961 \cdot S + 0.679 \cdot M_1 + 1.952 \cdot M_3 + 0.522 \cdot \alpha_{L1} + 1.121 \cdot M_4$; $h_{D3} = 1.312 - 1.531 \cdot S - 1.532 \cdot M_1 + 5.41 \cdot M_3 - 3.988 \cdot \alpha_{L1} + 0.311 \cdot M_4$.				

The cross-validation procedure was used to correctly apply the discriminant model. The corrected training set (obtained by excluding daily WCPs incorrectly assigned to a certain class) was used to construct discriminant functions and simple classification functions. The test sample was formed by daily WCPs excluded from the training sample due to incorrect classification. On the basis of the obtained classification functions, the re-classification of objects that were not included in the training sample was carried out. As a result of their regrouping in accordance with the calculated values of the classification functions, the final classification was obtained. The application of the DA method provided a refinement of the results of the classification obtained by the K-means method and the formation of samples of daily WCPs by season and type of day.

4.5. Formation of Typical Water Consumption Profiles and Their Description

The formation of the similar type groups for daily WCP provides the possibility to form samples of retrospective data and use them for a formalized description of typical conditions of water consumption.

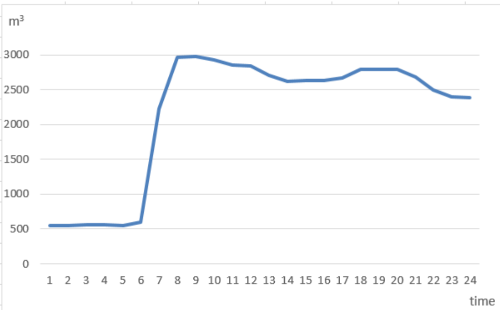
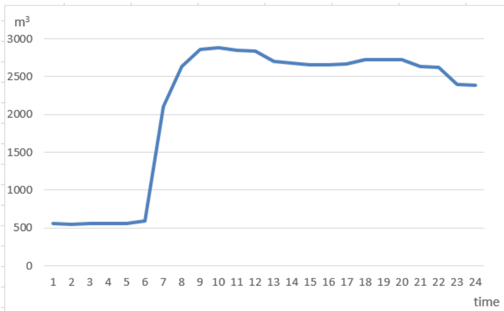
The sets of similar daily WCPs were used to refine the equations for the components of daily water consumption for typical days. Therefore, daily WCP samples were formed for typical days and the principal component method was applied. This made it possible to obtain the equation for the corresponding daily WCP components for a typical day (Table 11).

Table 11. Equation of water consumption components of typical days.

Interpretation of the Principal Components	Day Type	
	Workday	Weekend
Water consumption in the day time	$Z_1 = \sum_{i=8}^{21} z(t_i)$	$Z_1 = \sum_{i=9}^{22} z(t_i)$
Water consumption in the interim period of the day	$Z_2 = \sum_{i=(7,22,23,24)} z(t_i)$	$Z_2 = \sum_{i=(7,8,23,24)} z(t_i)$
Water consumption in the night time of the day	$Z_3 = \sum_{i=1}^{6} z(t_i)$	$Z_3 = \sum_{i=1}^{6} z(t_i)$

In addition, the sets of similar daily WCPs were used to determine the average characteristics of water consumption and to build typical daily WCPs for typical days in each typical season (Table 12). The shape of typical daily WCPs is described using morphometric parameters.

Table 12. A fragment of the results of the formalized description of daily WCP for typical days (on class 3rd by season).

Parameter	Day Type	
	Workday	Weekend
Typical daily WCP		
Z, m^3	51,629	51,105
Z_1, m^3	38,877	40,854
Z_2, m^3	9513	6892
Z_2, m^3	3369	3359
α_{L1}	179.02	169.65
M_1	0.32	0.37
M_2	0.65	0.69
M_3	0.50	0.525
M_4	0.86	0.89

It should be noted that the analysis of typical daily WCPs showed that the average daily water consumption for weekdays and weekends within each season differs only slightly. However, the shape of the profiles is different and is characterized by a shift in the maxima of the daily WCPs on weekdays compared to the daily WCPs on weekends. In addition, the daily WCPs on weekends are less erratic than on weekdays. This is confirmed by the morphometric analysis of the shape of typical daily WCPs for weekdays and weekends in each season and the results of the description of their shape.

The obtained results are the initial information both for monitoring the operation of the WSS within the CMFMCs of the megapolis and for planning their water supply, adjusting the operation schedules of water supply facilities considering the actual conditions of water consumption, as well as planning energy consumption and monitoring its efficiency. The organization of water consumption monitoring in the CMFMCs will make it possible to refine the parameters of typical daily WCPs on typical days to plan the operation of WSS and manage its energy efficiency.

5. Discussion and Conclusions

Effective use of energy and natural resources is one of the priority areas of sustainable development of the city and achieving the goals of reducing greenhouse gas emissions. Ensuring the energy efficiency of UISs is one of the tools for reducing final energy consumption in the urban production sector. WSS is an important component of the city infrastructure, which ensures the vital activities of the city population, and is also a large consumer of energy (electricity) and natural (water) resources. The effectiveness of the operation of WSS and its facilities in CMFMCs depends on timely response to changes in water demand. Ensuring the energy efficiency of WSS operation requires taking into account the dynamics of daily water demand for effective planning of the operation of water supply facilities and the consumption of energy resources, taking into account cyclical changes in the technological process in accordance with the requirements of the standards of ISO 50000 series. Monitoring of water demand and development of principles to determine the influence of social, climatic, and seasonal factors on the irregularity and cyclicity of demand is one of the operation efficiency components of WSS within CMFMCs.

Household water consumption is crucial for WSS in CMFMCs. Current water consumption determines the technological parameters of the water supply process, the schedule of operation of pumping stations and control units, and the hydraulic parameters of the water distribution network. Therefore, water consumption determines the operating conditions of water supply facilities. Water consumption is irregular throughout the year and day and is influenced by seasonal, climatic, and social factors. Thus, environmental factors influence the efficiency of the water supply process and the operation of water supply facilities. Identification and formalization the influence of seasonal, climatic, and social factors on changes in water consumption is the basis for water supply planning, adjustment of the operation schedules of water supply facilities, and electricity consumption planning and control.

The main indicator of the water consumption process is daily WCPs. The analysis of daily WCPs suggests that water consumption varies depending on the season and the type of day of the week. The analysis of daily WCPs and the identification of hidden regularities that determine the formation of water consumption in the megapolis CMFMCs are necessary to identify typical operating conditions for water supply facilities, considering the influence of seasonal and social factors. The solution to the problem of identification and formalization of such patterns is based on the application of the theory of pattern recognition and involves the phased use of automatic classification methods "without teacher" and classification "with teacher" to identify typical classes of the same daily WCPs. The basis of the analysis is the formation of a DB, which contains a set of characteristics of daily water consumption and its irregularity, as well as the morphometric parameters that describe the shape of daily WCPs. Water consumption has a clearly defined daily cycle, reflecting the cyclical nature of the daily lifestyle of the population. The application of the principal component method ensured the determination of the contribution of hourly values of water consumption to the daily WCPs configuration and the formation of equations for the dominant components of daily water consumption. The resulting equations allow the determination of water consumption quantities for the characteristic periods of the day, which contributes to the expansion of the information feature space describing daily water consumption. The formation of classification characteristics is carried out taking into account the peculiarities of the influence of external factors on water consumption. The characteristics of daily WCPs in terms of water volumes were used to identify the influence of seasonality. The description of the form of daily WCP is used to identify the influence of social factors. The generated sets of classification features form the basis for the daily WCPs classification procedure in two stages: (1) according to the influence of seasonality; (2) according to the influence of social factors (type of day). At the same time, the results of the first stage are taken into account during the formation of samples of daily WCPs for their classification at the second stage.

The use of cluster analysis made it possible to obtain important information about the characteristics of water consumption depending on the season of the year and changes in the rhythm of life of the population of the megapolis on weekdays and weekends. The use of the hierarchical CA method provided the identification of the similarity of daily WCPs depending on the season and the type of day of the week. The results of the hierarchical CA method show a tendency to combine daily WCPs typical for a given season into one class. This confirms the influence of seasonality on the nature of water consumption. In addition, the results of the hierarchical CA method demonstrate a tendency to combine daily WCPs typical of the working day and the weekend in one class, confirming the influence of social factors. The use of the k-means method confirmed the assumption of differences in daily WCPs depending on the season and type of day and allowed the formation of groups of daily WCPs of similar types. The results obtained indicate the validity of the classification results, as well as the homogeneity and significance of the contribution of classification variables to the distribution of daily WCPs into groups. The results of automatic classification were used to refine the division of daily WCPs into groups using the DA method. The use of the DA method provided the formation of a set of discriminant variables that best distinguished the daily WCPs from the different groups, the interpretation of the differences between the groups, and the formation of classification functions to predict the probability that the daily WCPs belong to the corresponding class. The results of the DA method confirmed the statistical significance of discrimination, the significance and information content of the classification variables. The solution to the problem of searching for hidden regularities in the change of the nature of water consumption using the theory of pattern recognition ensured the formation of sets of the same type of daily WCPs, taking into account seasonal and social factors, the objects of which are unambiguously consistent with the chosen interpretation of their differences.

The formation of sets of similar daily WCPs allows to carry out of a formalized description of water consumption for the obtained classes. The result of such description is the determination of average characteristics of daily water consumption for each season and the formation of average daily WCPs for the obtained typical classes (one typical daily WCP for each typical day of a typical season) and their description. In addition, the results of the formation of groups of similar types of daily WCPs provided a refinement of the components of daily water consumption considering the type of day. The obtained results are the initial information for the implementation of effective water supply planning and adjustment of the schedule for switching on and off the pumping units of pumping stations taking into account the daily cycle of water consumption of the CMFMCs, as well as for the management of energy efficiency of the WSS. Taking into account the obtained results will contribute to the supply of water in the required volume according to the need, taking into account the season and the day of the week, and therefore will ensure the reduction of water losses and electricity consumption in WSS. The organization of ongoing monitoring of water consumption will contribute to the collection of information on daily WCPs, which will clarify the results of their classification and a formalized description of the typical operating conditions for the WSS facilities within the CMFMCs.

The identification of daily WCPs of a similar type makes it possible to determine the time ranges corresponding to certain operating conditions of water supply facilities. In future studies, the obtained results will be used to sample historical data in order to create a set of models of the energy baseline adapted to the actual conditions of operation of WSS within CMFMCs in accordance with the requirements of the standards of the series ISO 50000. At the same time, the determination of the energy baseline requires the development of a procedure for identifying cyclical changes in water consumption, identifying inconsistencies in the planning process, and correcting the planned values of water supply taking into account the influence of anomalous climatic factors.

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Nomenclature

Sets		
T	-	random process observation period
j	-	day number
i	-	time number
n	-	number of points (points of time) for fixing water consumption values
s	-	number of constituent (principal) component
m	-	number of variables
Parameters		
t	-	time of day (h)
z_j	-	value of water consumption to *i*-th time moment (m^3)
$Z,$	-	daily water consumption (m^3)
Z_1	-	water consumption in the day time (m^3)
Z_2	-	water consumption in the interim period of day (m^3)
Z_3	-	water consumption in the night time of day (m^3)
Z_{max}	-	maximum value of daily water consumption (m^3)
Z_{min}	-	minimum value of daily water consumption (m^3)
$Z_{min,d}$	-	minimum value of daily water consumption in the day time (m^3)
Z_{ms}	-	mean square value of daily water consumption (m^3)
Z_m	-	mean value of daily water consumption (m^3)
$Z_{m,d}$		mean value of daily water consumption in the daytime (m^3)
σ^2	-	variance of daily water consumption (m^3)
σ_d^2	-	variance of daily water consumption in the daytime (m^3)
σ	-	standard deviation of daily water consumption (m^3)
K_{forms}	-	WCP forms coefficient
K_{max}	-	WCP maximum coefficient
K_{fill}	-	WCP fill coefficient
K_{irreg}	-	WCP irregularity coefficient
(x_i, y_i)	-	coordinates of the vertices of the polygon reflecting the RC
(x_c, y_c)	-	coordinates of the weight center RC
d	-	weight center translation
P	-	perimeter RC
P_{conv}	-	perimeter of the convex hull circumscribed around the RC
S	-	area RC
S_{conv}	-	area of the convex hull circumscribed around the RC
α_i	-	angle corresponding to *i*-th time moment (°)
α_{L1}	-	elongation axis angle RC (°)
R_{min}	-	inner circle RC radius
R_{max}	-	outer circle RC radius
L_1	-	length of the main axis RC elongation
L_2	-	the length of perpendicular to main axis RC elongation

M_1	-	roundness RC
M_2	-	compactness RC
M_{2conv}	-	compactness of the convex hull circumscribed around the RC
M_3	-	elongation RC
M_4	-	convexity RC
h_s	-	classification function for season
h_D	-	classification function by type of day

Appendix A. Description of the Daily WCP

The transformation of daily WCP into the RC (Figure A1) is carried out by connecting the vertices of the polygon, the coordinates of which for each i-th hour ($i \in [1; n]$, $n = 24$) in the direction of their bypass are defined as [73]:

$$(x_i, y_i) = (z_i \cdot \sin \alpha_i, z_i \cdot \cos \alpha_i) \quad \text{(A1)}$$

Angle corresponding to the i-th hour:

$$\alpha_i = \frac{2 \cdot \pi \cdot i}{n} \quad \text{(A2)}$$

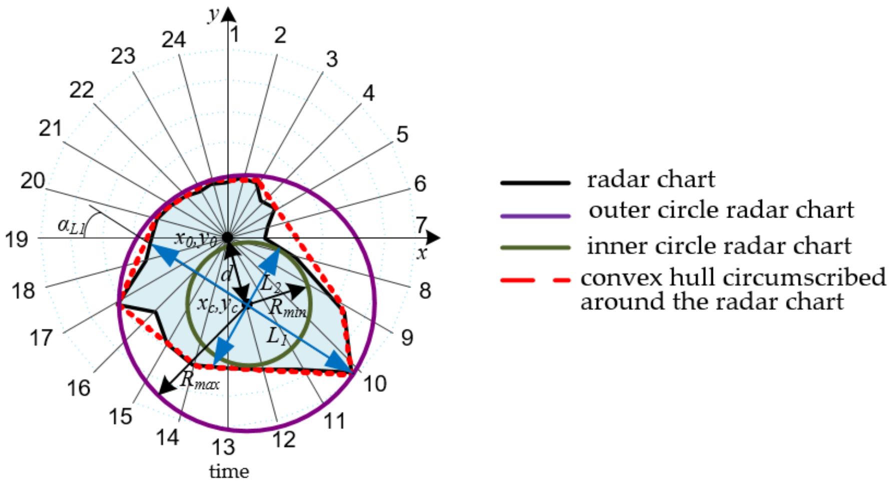

Figure A1. Daily WCP in RC form and graphical visualization of morphometric description [73].

Table A1. Daily WCP description parameters.

Classic Indicators		Morphometric Parameters	
Overall value	$Z = \sum\limits_{i=1}^{n} z_i$	Area	$S = \frac{1}{2} \sum\limits_{i=1}^{n} (x_i + x_{i+1})(y_i - y_{i+1})$
Mean value	$Z_m = \frac{1}{n} \sum\limits_{i=1}^{n} z_i$	Perimeter	$P = (x_n - x_1)^2 + (y_n - y_1)^2 + \\ + \sum\limits_{i=1}^{n-1} (x_{i+1} - x_i)^2 + (y_{i+1} - y)^2$
Mean square value	$Z_{ms} = \sqrt{\frac{\sum_{i=1}^{n} z_i^2}{n}}$	Weight center	$x_c = \frac{\sum_{i=2}^{n} \frac{x_i - x_{i-1}}{2(x_i \cdot y_{i-1} - x_{i-1} \cdot y_i)}}{1{,}5 \sum_{i=1}^{n} (x_i \cdot y_{i-1} - x_{i-1} \cdot y_i)}$ $y_c = \frac{\sum_{i=2}^{n} \frac{y_i - y_{i-1}}{2(x_i \cdot y_{i-1} - x_{i-1} \cdot y_i)}}{1{,}5 \sum_{i=2}^{n} (x_i \cdot y_{i-1} - x_{i-1} \cdot y_i)}$
Variance	$\sigma^2 = \frac{1}{n-1} \sum\limits_{i=1}^{n} (z_i - Z_m)^2$	Weight center translation	$d = \sqrt{(x_0 - x_c)^2 + (y_0 - y_c)^2}$
Standard deviation	$\sigma = \sqrt{\sigma^2}$	Roundness	$M_1 = \frac{R_{min}}{R_{max}}$

Table A1. *Cont.*

Classic Indicators		Morphometric Parameters	
Forms coefficient	$K_{forms} = \frac{Z_{ms}}{Z_m}$	Compactness	$M_2 = \frac{4 \cdot \pi \cdot S}{P^2}$
Maximum coefficient	$K_{max} = \frac{Z_{max}}{Z_m}$	Elongation	$M_3 = \frac{L_2}{L_1}$
Fill coefficient	$K_{fill} = \frac{Z_m}{Z_{max}}$	Elongation angle	$\alpha_{L1} = \tan^{-1} \frac{y_c - y_{max}}{x_c - x_{max}}$
Irregularity coefficient	$K_{fill} = \frac{Z_{min}}{Z_{max}}$	Convexity	$M_4 = \frac{S_2}{S}$

The main diagonal of the polygon passes through the RC point with coordinates (x_{max}, y_{max}) and center of gravity (x_c, y_c). The additional diagonal of the polygon passes through the perpendicular to the main diagonal at the center of the RC gravity. The length of the polygon axes is defined as the distance between the RC points that are the ends of the axes:

$$L = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \quad \text{(A3)}$$

The task of determining the length of the main diagonal is reduced to determining the RC point, which belongs to the line described by the equation:

$$\frac{x - x_{max}}{x_c - x_{max}} = \frac{y - y_{max}}{y_c - y_{max}} \quad \text{(A4)}$$

The task of determining the length of the additional diagonal is reduced to determining the RC point, which is the solution to the equation:

$$x(x_c - x_{max}) + y(y_c - y_{max}) = 0 \quad \text{(A5)}$$

The task of constructing the convex hull of the RC is the task of constructing the minimal convex hull of the set of points X. The convex hull in the plane is a convex polygon whose vertices are a subset of the RC vertices. For its construction, standard algorithms (such as Graham's and Jarvis's) are used.

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