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A Supply Chain Ecosystem Approach to Smart City Manufacturing Clusters: Digital Transformation-Enabled Energy Management in Urban Water Systems

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Abstract

This study develops a supply chain ecosystem (SCE) approach for smart city manufacturing clusters (SCMCs) through the integration of digital technologies into energy management of urban water systems (UWSs). The proposed framework integrates the Internet of Things (IoT), blockchain, and machine learning (ML) analytics within a smart water grid architecture to support sustainable and energy-efficient water supply management. Its principal contribution is an SCE-oriented information and analytical framework linking distributed system entities and stakeholders through integrated data management and decision support. To address the hierarchical and multi-objective nature of the energy management problem, a stratified representation approach is proposed, enabling decomposition into interconnected subproblems and improving coordination across multiple system levels within the SCE. An information-analytical system is developed, integrating subsystems for data acquisition, processing, storage, analysis, planning, monitoring, and decision support. The proposed architecture combines IoT-enabled real-time data acquisition with blockchain-based mechanisms supporting data integrity, traceability, and verifiable information exchange among system entities. Energy planning is formalised through the construction of an energy baseline (EnB) accounting for system hierarchy, operational constraints, and planning horizon. The operational application of the framework is demonstrated using a case study of a water intake facility. GMDH (Group Method of Data Handling) neural networks are applied to model energy consumption, while multi-criteria analysis identifies a second-order polynomial activation function as optimal, achieving high predictive accuracy (MAPE = 0.513%; RMSPE = 0.595%). The resulting day-ahead EnB, based on planned technological parameters and pump operation schedules, demonstrates how the proposed SCE framework translates integrated data management into operational decision support for energy-efficient UWS operation.

Keywords: urban manufacturing; sustainability; smart city; supply chain ecosystem; urban water system; energy efficiency; IoT

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1. Introduction

Urbanisation processes, the expansion of large cities, and the necessity to ensure the continuous supply of everyday consumer goods have stimulated the development of smart city manufacturing clusters (SCMCs). The formation of such clusters is aimed at reducing the spatial gap between producers and consumers, improving the efficiency of urban logistics systems, decreasing transport flows, and mitigating pressure on urban transport infrastructure [1,2]. The broader field of urban production has examined the integration of manufacturing activities into urban environments, including the development and spatial organisation of urban factories [3,4]. Urban manufacturing has also been investigated from the perspectives of value-chain configuration, sustainability, and circular urban development [5,6]. SCMCs are located within residential areas of large cities and incorporate urban infrastructure of various purposes, including buildings intended for residential use, public organisations, manufacturing facilities, and service enterprises [7], as well as urban infrastructure systems (UISs), which comprise electricity and gas supply systems, transport systems, water supply systems, and wastewater infrastructure [8,9]. UISs constitute an essential component of the efficient functioning of SCMCs, as well as of the viability and social development of metropolitan areas. At the same time, climatic, territorial, and social factors, together with the lifestyle patterns of the urban population, determine the operational conditions of UISs [9,10].

Within SCMCs, the interaction of manufacturing, logistics, service, infrastructural, and information subsystems forms a complex supply chain ecosystem (SCE), characterised by interconnected material, energy, information, financial, and service flows [7]. From the SCE perspective, urban infrastructure systems should not be considered as isolated technical facilities but as interconnected components of a distributed urban ecosystem supporting manufacturing activities, logistics operations, service processes, and the daily needs of the urban population. The efficiency, resilience, and sustainability of SCMCs depend on the coordinated functioning of interconnected infrastructure systems and on the effective management of resource and information flows across the entire ecosystem.

Contemporary urbanisation trends contribute to the expansion and increasing complexity of UIS structures, accompanied by rising consumption of energy and natural resources. Growing demand for energy and resources necessitates the transition towards a society based on the principles of sustainable development. The implementation of sustainability principles and the achievement of climate neutrality objectives require the decarbonisation of all economic sectors, improvements in energy efficiency, and reductions in final resource consumption [11]. In this context, the efficient utilisation of energy and natural resources within UISs represents one of the key principles for reducing environmental impact and ensuring sustainable urban development [12]. From the SCE perspective, sustainable development within SCMCs requires coordinated management of interconnected infrastructure systems, integration of digital technologies, and adaptive management of resource flows across multiple operational levels and stakeholders [7].

Urban water systems (UWSs) ensure the supply of potable water to end users within SCMCs and constitute one of the critical life-support systems of modern cities [13]. Within the SCE framework of SCMCs, UWSs support not only residential consumers but also manufacturing, logistics, and service operations requiring stable and reliable water supply conditions. The implementation of water supply processes requires substantial consumption of both energy and natural resources [10,14]. Rational utilisation of water and energy resources in UWSs remains essential for ensuring the sustainable operation of UISs [10] and reducing CO_2 emissions [15].

Pumping stations are among the most energy-intensive components of UWSs [13,16]. Optimisation of pump operating regimes and improvement of pumping station energy

efficiency are widely investigated as approaches to reducing energy consumption [15,16]. Pressure management in water distribution networks to minimise leakages and water losses [17], together with the assessment of end-user water consumption and consumption profiles [9,18], are also regarded as important mechanisms for the rational use of water resources in UWSs. Considering the strong interconnection between water, energy, and carbon systems [14], achieving energy efficiency and reducing final energy consumption in UWSs requires a comprehensive and integrated approach. In this regard, the organisation of effective energy management has become increasingly important for improving the energy efficiency of UWSs and ensuring the sustainable operation of UISs [19,20]. From the SCE perspective, energy management should support coordinated interaction between distributed infrastructure facilities, digital platforms, operational decision-making processes, and ecosystem stakeholders, including water utilities, manufacturing facilities, logistics nodes, service enterprises, and municipal authorities.

The development of Industry 4.0 digital technologies and their integration into UWSs contribute to the digitalisation of water infrastructure and the implementation of the Water 4.0 concept, aimed at improving resource efficiency, energy performance, and water supply resilience [21,22]. In particular, the Internet of Things (IoT) is considered a key instrument for data acquisition, including real-time monitoring [22,23]. The analysis of collected data forms the basis for decision-making processes supporting efficient water supply management [21]. However, the increasing number of IoT devices results in a rapid growth in the volume of data requiring processing and analysis. This necessitates the application of advanced data analytics methods and intelligent analytical tools capable of generating optimal solutions for specific operational contexts [22]. Furthermore, the increasing number of connected devices and the predominantly centralised IoT infrastructure raise concerns regarding data security, privacy, interoperability, and operational reliability [24,25]. The integration of blockchain technology with IoT has therefore been proposed supporting data integrity and traceability, preserving data integrity, ensuring secure decentralised data management, and supporting coordination between distributed computational agents within the SCE environment [23,26]. At the same time, the reliability of IoT-based smart water networks and their connected components remains an important consideration for dependable system operation [27]. The implementation of the Water 4.0 paradigm requires the integration of multiple digital technologies to ensure efficient and secure collection, storage, analytical processing, and exchange of large volumes of operational data for improving UWS energy efficiency and sustainable water supply management within SCMCs [25].

However, existing studies provide limited integration of these technological and analytical functions within an SCE-oriented framework that simultaneously addresses data management, information integrity, hierarchical energy planning, and decision support across interconnected UWS entities and stakeholders. In particular, a research gap remains in linking IoT-enabled data acquisition and blockchain-supported data integrity and traceability with intelligent analytics for coordinated energy management within SCMCs. This study addresses this gap through an integrated information and analytical framework in which these technologies serve as enabling mechanisms for coordinated data management and decision support.

This study is aimed at advancing the methodology of energy management within the Water 4.0 paradigm to support sustainable water supply for SCMCs and urban areas as a whole. The objective of the study is to develop an SCE-oriented information and analytical framework for coordinated data management and decision support in UWS energy management, integrating IoT and blockchain technologies with machine

learning-based intelligent analytics, and to demonstrate its operational application for energy planning in UWSs.

The main contributions of this study are as follows:

1. An SCE-oriented approach to UWS energy management is developed to support coordinated interaction among urban water infrastructure, system entities, and stakeholders through integrated data management and analytical decision support within the SWG paradigm.
2. An information and analytical architecture for energy management within the SCE is proposed, combining IoT and blockchain technologies for reliable data acquisition from distributed metering devices across UWS facilities and data integrity, traceability, and verifiable data exchange between computational agents performing monitoring, planning, coordination, and control functions related to water supply and energy consumption processes within SCMCs.
3. An approach to energy consumption planning in UWSs is proposed, considering both the hierarchical level of water supply infrastructure and the selected planning time horizon, with practical implementation demonstrated through a case study of a water intake facility supplying an urban district.
4. As an operational implementation of the proposed framework, Group Method of Data Handling (GMDH) neural networks (NN) are applied to develop an energy baseline (EnB) model for a water intake facility. The modelling results based on experimental data demonstrate the predictive performance of the developed GMDH-based EnB model under the investigated operating conditions.

The remainder of this paper is organised as follows. Section 2 presents a literature review and substantiates the role of IoT, blockchain technology, and intelligent data analytics tools within the contemporary paradigm of intelligent UWSs and sustainable water supply management. Section 3 describes the materials and methods underlying the proposed approach to energy consumption planning in UWSs, including the information and analytical support framework for energy management based on the integration of IoT and blockchain technologies. Section 4 presents the research results. The final section discusses the findings and provides concluding remarks.

2. Literature Review

2.1. Features of Modern Urban Water System Operation

UWSs have a complex and highly branched structure comprising numerous elements involved in the water supply process [9]. UWSs are required to satisfy the water demand of different categories of consumers within SCMCs at any point of the water distribution network, ensuring the required pressure and uninterrupted supply at all times [13]. Within SCMCs, UWSs should be considered an integral component of the SCE, supporting not only residential water consumption but also manufacturing, logistics, and service operations dependent on stable and reliable water supply conditions. Recent urban-production studies further emphasise the interdependence of manufacturing activities, value-chain configurations, and cross-domain urban flows [28,29], supporting the consideration of infrastructure systems as interconnected components of the urban production environment. The stochastic nature of water consumption complicates the management of water supply processes and the operational modes of UWS structural components [22], resulting in the risk of water surplus or shortage within the network at particular time intervals.

The requirement for a reliable and sustainable water supply to SCMC consumers creates the need for intelligent operational management systems [22,30]. The operating conditions of UWSs, together with sustainability and energy-efficiency requirements, determine the necessity of applying advanced technologies for monitoring, analysing, and

controlling water supply processes [21]. From the SCE perspective, effective management of UWSs requires coordinated interaction between distributed infrastructure facilities, metering devices, analytical platforms, and decision-making agents responsible for maintaining the continuity and efficiency of water supply processes within SCMCs.

Information and communication technologies, including water quality, pressure, and flow sensors, smart water meters, automatic meter reading technologies, and advanced metering infrastructure, are increasingly integrated into water distribution networks to improve the operational efficiency of UWS components [13,31]. These technologies are applied for monitoring UWS parameters, controlling and optimising water supply processes, including water abstraction, treatment, and distribution, as well as electricity consumption associated with water supply operations [32]. The ability of measurement devices to collect and transmit data in real time [31], combined with advanced data analytics for decision support, enhances the efficiency of SWG management processes [21]. The integration of data acquisition, storage, and analysis technologies, infrastructure monitoring systems, digital control of SWG structural elements, and SCMC water supply management is increasingly based on the application of the IoT [27]. Within the SCE framework, IoT technologies support continuous information exchange and operational coordination between distributed infrastructure elements and ecosystem participants involved in water supply management processes. Recent studies have extended blockchain applications to water management by integrating distributed ledgers with IoT-based monitoring and data-management architectures [33,34].

SWGs are therefore considered an integration of Internet-based technologies with intelligent devices and sensors located throughout water distribution networks, enabling real-time monitoring and data transmission to supervisory systems [22,35]. Advanced metering infrastructure involves the deployment of large numbers of smart meters installed at the consumer level and supports the collection of detailed water consumption data [36,37]. Data obtained from smart meters and IoT sensors enable identification of water consumption patterns [37], detection of network failures and water leakages [38], and improvement of the efficiency, resilience, sustainability, and coordination of SCMC water infrastructure management within the SCE environment, thereby supporting implementation of Sustainable Development Goals (SDGs) related to clean water, clean energy, sustainable urban infrastructure, and climate action.

2.2. Energy Management in Urban Water Systems

The UWS management system should ensure coordinated operation with other urban infrastructure systems, particularly electricity supply systems. Within SCMCs, UWSs should be considered an integral component of the SCE, interacting with manufacturing, logistics, service, and energy subsystems through interconnected resource and information flows. The operational efficiency of UWSs affects not only water supply reliability but also the continuity and sustainability of SCMC operational processes.

The operational efficiency of UWSs depends on a range of internal factors, including the technical condition and performance of structural components, as well as external factors, such as social, climatic, and geographical conditions, which may result in suboptimal operation of water supply facilities and the entire system [13]. The smart water grid (SWG) concept involves managing water supply processes to ensure reliable water distribution, including the delivery of water of the required quality and quantity, while simultaneously improving energy efficiency. The specific characteristics of water supply processes within SCMCs, where water is considered both a product and a natural resource, directly influence electricity consumption in UWSs [9,20]. From the SCE perspective, efficient operation of

UWSs requires coordinated management of water, energy, information, and service flows across interconnected infrastructure facilities and ecosystem participants.

The efficiency of natural resource utilisation (water) and energy consumption (electricity) in UWSs depends on effective planning of water supply operations and operating modes of system components [20]. These processes should consider current and forecasted water demand patterns within SCMCs. Incomplete or inaccurate information regarding water consumption may lead to errors in water supply planning and operational management [9]. Water demand forecasting therefore represents an important component of effective planning and management of both water supply and electricity consumption processes [9,19]. Maintaining a balance between the volume of water supplied to the network and actual water demand within SCMCs enables the reduction in inefficient water and electricity consumption in UWSs. Consequently, energy management systems should ensure integrated optimisation of operational parameters, system structure, and operating modes according to technical, social, economic, and environmental criteria [21]. Within the SCE framework, such optimisation should support coordinated decision-making between distributed infrastructure facilities, operational management systems, and ecosystem stakeholders involved in water supply and energy consumption processes.

Energy management involves systematic planning and control of water supply processes, including water abstraction from sources, treatment, transportation to consumers, utilisation of production capacities, electricity consumption, and operation of UWS components such as pumping stations, pipeline systems, water treatment facilities, and reservoirs. The implementation of energy management tasks in UWSs requires the continuous execution of interconnected processes, including data acquisition and visualisation, data analysis and forecasting, and control and optimisation of water supply operations and electricity consumption. IoT technologies enable monitoring, measurement, and control of water and electricity use at all stages of the water supply process and therefore support continuous data acquisition and exchange [27]. Within the SCE environment, IoT technologies also facilitate operational coordination and information exchange between distributed infrastructure components, digital platforms, and decision-making agents responsible for water supply management. The analysis of collected data constitutes the basis for operational decision-making processes [21,26]. In this context, water demand planning within SCMCs should be integrated into energy management systems to optimise water supply and electricity consumption processes, improve service quality, reduce the risks of failures and water leakages, and increase the efficiency of natural and energy resource utilisation [19]. Moreover, from the SCE perspective, the integration of water demand forecasting, infrastructure monitoring, and energy planning enables coordinated and adaptive management of interconnected urban infrastructure systems under dynamic operational conditions.

2.3. Intelligent Data Analytics Technologies in Smart Water Grids

The SWG concept involves the creation of an intelligent operational environment based on the IoT, integrating smart metering devices and automated control mechanisms within urban water systems [31]. Within SCMCs, SWGs should be considered part of the broader SCE, supporting coordinated management of water, energy, information, and service flows across interconnected infrastructure facilities and ecosystem participants. Monitoring, optimisation, and control strategies in SWGs are implemented through continuous data analysis and intelligent decision-support mechanisms. The application of IoT-based smart metering technologies enables the collection of heterogeneous operational data from distributed UWS infrastructure components [36]. Data obtained from UWSs within SCMCs play an important role in supporting operational decision-making processes in SWGs [26,39], as well as infrastructure maintenance and long-term system develop-

ment [19]. At the same time, the large number of distributed IoT devices significantly increases the volume of operational data requiring storage, processing, and analysis. The extraction of useful information for decision-making therefore requires advanced analytical methods and appropriate interpretation of collected data, creating the need for intelligent tools and data-driven strategies supporting water supply management within the SCE environment.

Advanced digital technologies, including big data analytics, cloud computing, intelligent data mining, ML, and digital twins, are increasingly applied for processing and analysing large volumes of data generated by IoT devices in SWGs [31,39]. Large-scale operational data obtained from distributed IoT infrastructure is typically transmitted to remote cloud computing environments and data centres for storage and analytical processing. Cloud computing technologies provide scalable data storage resources and computational capabilities for the deployment of advanced analytical platforms and information modelling systems [22,40]. Intelligent data analytics involves data processing procedures, including filtering, anomaly detection, transformation, aggregation, and pattern extraction, using various analytical methods and algorithms to identify hidden relationships and generate new operational knowledge [41]. Within the SCE framework, these technologies support coordinated information exchange and analytical interaction between distributed infrastructure facilities, computational agents, and ecosystem stakeholders involved in water supply and energy management processes.

Big data analytics (BDA) within the SWG domain enables the identification of operational problems in water distribution networks. It supports efficient and adaptive decision-making processes related to water and energy management [39]. The analysis of smart meter data facilitates the identification of water consumption trends within SCMCs, including the influence of climatic and seasonal factors, and supports the construction of daily water consumption profiles [9], water demand models, and forecasting systems [22,36]. Based on BDA, SWGs can rapidly detect water leakages, generate automated leakage alerts, and dynamically regulate water supply and distribution according to forecasted demand patterns [36,42]. From the SCE perspective, such analytical capabilities improve coordination between interconnected infrastructure systems and enhance the adaptability and operational resilience of SCMCs under dynamic demand conditions.

ML algorithms have become one of the key instruments for intelligent management in SWGs [25,43]. Supervised, unsupervised, semi-supervised, reinforcement learning, and deep learning methods are applied for the development, calibration, and validation of analytical and predictive models [43]. The capability of ML algorithms to process large volumes of heterogeneous data and identify complex relationships within operational datasets can improve modelling accuracy and support adaptive management processes [19,44]. In SWGs, ML techniques are used to identify temporal and spatial dependencies within big data environments, detect hidden patterns, recognise anomalies, and improve the adaptability of monitoring, control, and management systems [36,45]. ML methods are also applied for analysing water consumption structures and profiles, short-, medium, and long-term forecasting of water demand within SCMCs, and prediction of energy consumption based on historical operational data [19,43]. Despite their ability to identify complex nonlinear and spatiotemporal relationships, existing ML-based approaches to energy-consumption forecasting have several limitations. Their predictive performance depends strongly on the quality and representativeness of historical data, while models developed for specific operating conditions may require recalibration or retraining under changing operational regimes or when transferred to other systems. These limitations motivate the use of modelling approaches capable of structural self-organisation and automatic selection of relevant input variables.

GMDH neural networks provide such capabilities by iteratively selecting model inputs and optimising model structure during model development, thereby supporting the representation of nonlinear relationships in complex operational data [46]. These capabilities are particularly relevant where model complexity, parameter tuning, and limited interpretability constrain the practical application of ML-based forecasting to operational energy-management decision-making [43,47]. GMDH-based models have been applied to energy-demand and energy-consumption forecasting [47], while recent studies demonstrate their applicability to other nonlinear forecasting problems [48,49].

The results of ML-based analytics support efficient SWG management. ML algorithms support the development of reliable predictive models of water consumption [37,43], enabling more efficient pump operation management, optimisation of water supply processes, reduction in water losses, and improvement of energy efficiency. Reliable and traceable data management is also important for data-driven water management systems, particularly where operational information is exchanged between distributed system components [50]. Within the SCE environment, reliable operational data and intelligent analytical systems constitute essential prerequisites for coordinated infrastructure management and adaptive decision-making processes across interconnected urban systems. In this context, blockchain provides a mechanism for supporting the integrity, traceability, and verifiability of telemetry data acquired from distributed IoT devices within UWS energy-management systems. Once registered in the blockchain environment, measurement records can be traced and verified during subsequent data exchange and analytical processing. The integration of blockchain with IoT-based sensing has also been investigated as an approach to reliable data management and information exchange in smart water systems, supporting water-distribution management and sustainable urban water-resource management [32].

Table 1 provides a comparative overview of representative IoT-, blockchain-, and ML-based approaches to smart water and energy management.

Table 1. Comparison of digital approaches to smart water and energy management.

Study	Main Application	IoT	Blockchain	ML/ Intelligent Analytics	Energy Management	Main Focus/ Limitation
Adedeji et al. [22]	Water 4.0 and digitalisation of water supply systems	Yes	No	Yes	Yes	Digitalisation of water systems; no integrated blockchain-based SCE framework
Al-Zoubi et al. [23]	Blockchain of Things for Water 4.0	Yes	Yes	No	No	Decentralised water-data management; limited analytical energy-management functionality
Slaný et al. [25]	Smart water management	Yes	No	Yes	No	IoT and AI integration rather than SCE-oriented energy planning

Table 1. *Cont.*

Study	Main Application	IoT	Blockchain	ML/ Intelligent Analytics	Energy Management	Main Focus/ Limitation
Sheeba et al. [26]	Autonomous urban water management	Yes	Yes	Yes	Yes	Integrated digital architecture; not structured around hierarchical SCE energy planning
Taloma et al. [36]	Smart water distribution systems	Yes	No	Yes	No	ML applications to water-system management
Li et al. [41]	Smart energy management	Yes	Yes	Yes	Yes	Broad smart-energy context rather than UWS-specific SCE energy management
Ahmed et al. [43]	Water-resources management	No	No	Yes	No	ML-based water-resource applications without integrated IoT–blockchain architecture
Chahardeh et al. [46] Srinivasan [47]	Energy-demand and consumption forecasting	No	No	Yes (GMDH)	Yes	GMDH-based forecasting without integrated UWS data-governance architecture
This study	SCE-oriented UWS energy management	Yes	Yes	Yes (GMDH)	Yes	Integrated data management, traceability, hierarchical energy planning, and operational decision support

The comparison shows that existing studies mainly address individual digital technologies or their combinations for water monitoring, data management, forecasting, and energy-related applications. Limited attention has been given to their integration within an SCE-oriented framework that combines data integrity and traceability with hierarchical energy planning and operational decision support. The proposed framework addresses this gap by integrating IoT-enabled data acquisition, blockchain-supported data management, and GMDH-based analytics within a unified SCE-oriented approach.

3. Materials and Methods

3.1. Structure of Blockchain-Based Energy Management Information-Analytical System

UWSs within SCMCs represent complex hierarchical systems comprising numerous structural components, each of which may itself be considered a complex system. Specific operational features, functional principles, optimisation objectives, and efficiency criteria characterise each hierarchical level. Within the SCE, UWSs interact with manufacturing, logistics, energy, and service subsystems through interconnected resource

and information flows, which increases the complexity of operational coordination and management processes. The primary objective of energy management is therefore to improve the operational efficiency of UWSs and their structural components within the integrated SCE environment.

The implementation of energy management tasks requires continuous monitoring of infrastructure conditions, registration of technological process parameters and energy consumption indicators, identification of factors influencing water demand within SCMCs and electricity consumption in UWSs, forecasting changes in the operational state of infrastructure facilities, supporting managerial decision-making, and evaluating the effectiveness of control actions. At the same time, contemporary energy management in UWSs is inherently multi-objective. It requires multi-stage planning of water supply and energy consumption processes, including day-ahead, hour-ahead, and real-time operational planning. Furthermore, the hierarchical structure of UWSs within SCMCs determines the hierarchical nature of energy management problems. The operational characteristics of infrastructure facilities and water supply processes at each UWS level should be explicitly considered during the development of energy management systems.

The complexity of UWSs and the multi-functional nature of energy management create the need to balance detailed system representation, required for accurate modelling of operational characteristics, with simplified problem formulations facilitating analytical processing and decision-making. To address this challenge, a stratified representation of complex systems is applied, enabling the description of the system through a set of characteristics corresponding to a particular abstraction level (stratum). Each stratum may contain its own objectives, subproblem structure, efficiency criteria, analytical model, and system representation using a set of characteristics providing an appropriate degree of detail for the selected abstraction level [51,52]. At the same time, the interconnections between objectives at different hierarchical levels and the global objective of the upper level are preserved.

The stratified representation approach for complex systems is applied in the development of the information and analytical system (IAS) for UWS energy management within the SCE framework. The global energy management problem is decomposed into a set of interconnected tasks, including tasks associated with different hierarchical levels of UWS infrastructure. Such decomposition simplifies the representation of physical infrastructure facilities at the information level, the implementation of application-level procedures and algorithms, and the formation of databases and data query mechanisms required for analytical and decision-support procedures [53]. The generalised architecture of the IAS for energy management within the SCE-oriented UWS environment is presented in Figure 1. The proposed architecture establishes the relationship between UWS energy-management tasks and the information and analytical resources required for their implementation, including operational data sources, data sets, analytical procedures, and decision-support components.

Figure 1 illustrates the principal data flows and communication interfaces within the proposed architecture. Operational data are transmitted from IoT-enabled measuring devices through the data acquisition subsystem to the blockchain-based information environment, where they are made available to databases and computational agents for analytical processing. Analytical outputs are subsequently exchanged between computational agents and decision-support components to support monitoring, forecasting, and control procedures.

The energy management IAS represents a set of methods, procedures, and analytical instruments for data acquisition, storage, processing, analysis, monitoring, control, and managerial decision support. All subsystems and their components, regardless

of their functional purpose or hierarchical level of application, are integrated within a unified information space. Within the SCE framework, this information space supports coordinated interaction between water supply infrastructure, energy systems, manufacturing facilities, logistics infrastructure, and computational agents involved in monitoring and management processes across SCMCs. The unified information space is implemented using a blockchain-based digital platform. The blockchain platform is developed using a distributed ledger architecture based on the Ethereum network. Programmable smart contracts and consensus mechanisms, including energy-efficient Proof-of-Stake (PoS), are deployed within the Ethereum environment across private, consortium, or testnet configurations such as Sepolia and Holesky. The underlying logic of these smart contracts and consensus mechanisms within the blockchain platform ensures transaction validation, protection against unauthorized record tampering, and automated distributed data management.

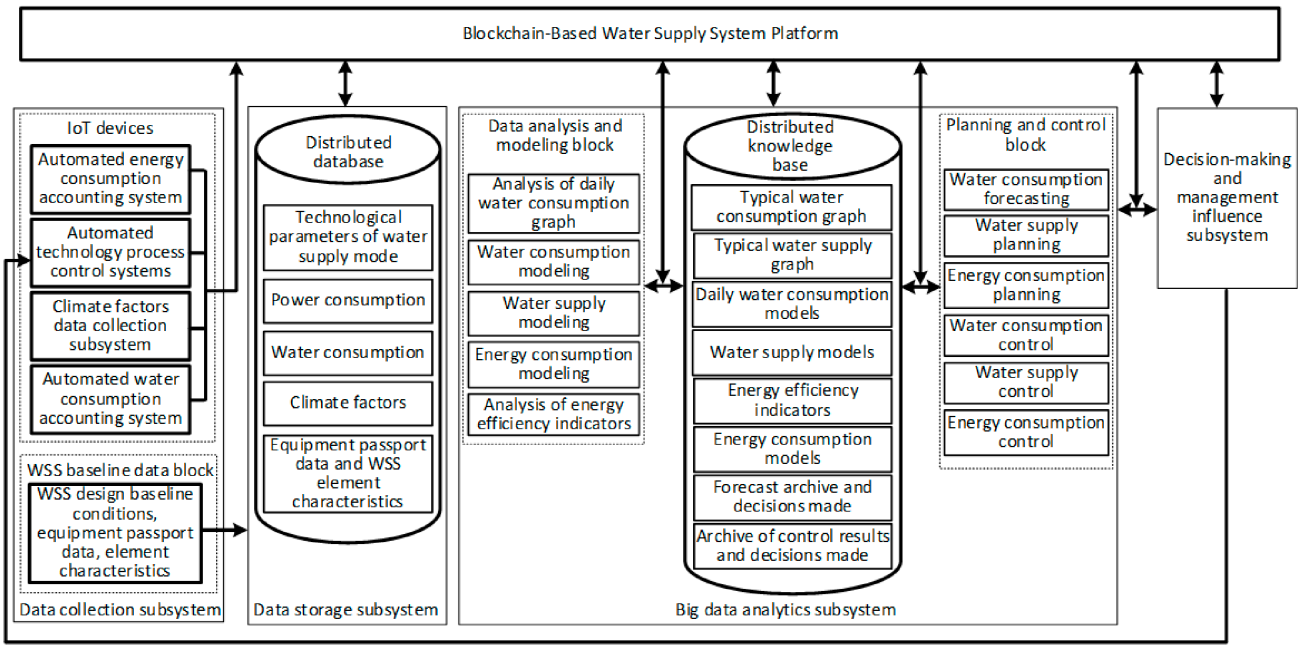


Figure 1. Architecture of the IAS for energy management within the SCE-oriented UWS environment.

Within the proposed architecture, blockchain does not directly perform energy optimisation or, by itself, ensure the overall cybersecurity of the IAS. Its role is to support data integrity, traceability, verifiable information exchange, and coordination between distributed system components and computational agents [33,54]. The practical relevance of blockchain depends on the organisational configuration and data-sharing requirements of the particular SCE. A blockchain-based architecture is particularly applicable where multiple organisationally independent entities require shared, traceable, and verifiable records without relying exclusively on a single data controller [54,55]. The present study does not empirically establish distrust or organisational fragmentation among stakeholders in the investigated UWS cases; therefore, decentralised trust is treated as an architectural assumption rather than as an empirically demonstrated requirement.

From a stakeholder perspective, the proposed SCE-oriented architecture involves UWS infrastructure operators, energy-system entities, manufacturing and logistics facilities, and computational agents with different functional roles in generating, exchanging, and using operational information. Blockchain-based data management can support distributed verification and traceability of shared records but introduces additional implementation and operational requirements associated with smart contracts, access and key management,

consensus mechanisms, and distributed-node maintenance [54,55]. These requirements should therefore be considered when selecting between blockchain-based and centralised data-management architectures for a particular SCE [54,55].

The IoT-based data acquisition subsystem ensures the integration of distributed metering devices, including sensors, flow meters, smart meters, and other intelligent measuring equipment installed throughout the water supply network. The subsystem supports data acquisition for individual UWS facilities, including water intake facilities, treatment plants, pumping stations, and other infrastructure components, as well as communication between control points and cloud services, data consolidation, processing, and information exchange. Within the SCE-oriented environment, the subsystem enables continuous monitoring of interconnected resource and operational flows across SCMCs. The application of smart contracts supports the identification and authentication of devices within the IoT network. Each measurement generated by an IoT device is registered in the blockchain as a separate cryptographically protected timestamped transaction, supporting data integrity and traceability. A preliminary data-validation mechanism is used to identify IoT device failures, anomalous measurements, and missing data. Detected events are assigned cryptographically secured status and time stamps and recorded on the blockchain, ensuring the integrity and traceability of the original records. Flagged data are processed using a Simple Moving Average with a 7-day window to account for weekly energy-consumption patterns, while the original blockchain records remain unchanged. Prolonged data absence is monitored through smart contracts, which generate a system alert and mark the corresponding IoT node as inactive when a predefined timeout is exceeded. Consensus mechanisms are applied to resolve conflicts between distributed nodes in the network. Consensus algorithms enable network nodes to establish a unified blockchain structure based on cryptographically linked blocks [35]. This approach supports data integrity and consistency throughout the distributed information environment [56]. Data obtained from IoT devices is integrated into a distributed database and subsequently processed within the BDA subsystem.

The BDA subsystem consists of a set of algorithms and analytical methods implementing computational procedures through specialised computational agents. Each computational agent is responsible for a specific analytical task, including formalised system description, pattern recognition and classification, modelling, forecasting, control, and decision support. Computational agents obtain the required information from the distributed database and operate within a strictly defined interaction framework with other agents. Interaction between computational agents and databases is performed through the blockchain platform, while consensus mechanisms ensure consistency and synchronisation of IAS within the SCE environment. The results generated by computational agents are stored in a knowledge base supporting managerial decision-making processes related to water supply and energy management. The knowledge base is continuously updated according to the outputs of computational agents and detected changes in data structures, including changes resulting from managerial control actions and operational modifications within the UWS infrastructure.

Within the SCE of SCMCs, the energy management IAS is designed as a modular, open, and interoperable system composed of interacting subsystems that support the integration of new objects and application-specific algorithms. The combined use of blockchain and IoT technologies enables traceable data acquisition and integrity-preserving data exchange from intelligent metering devices, reliable storage and exchange of operational information through distributed cloud services, and implementation of smart contracts and consensus mechanisms for communication between computational agents involved in monitoring and control of water supply and electricity consumption processes.

The proposed distributed data-management architecture reduces dependence on a single centralised point of failure and supports the integrity, traceability, and verifiability of registered data. Smart contracts and status tags enable automated recording of device failures and data anomalies, improving the transparency and auditability of data-management processes. The integration of stratified system representation with distributed data management provides a modular and scalable framework that supports configuration changes at both the information and physical infrastructure levels.

3.2. Methodological Aspects of Energy Consumption Planning in Urban Water Systems

3.2.1. Energy Consumption Planning Problem in Urban Water Systems

According to the EN ISO 50001 standard [57], the Plan–Do–Check–Act Deming cycle constitutes the foundation of energy management systems. Energy planning represents the first stage of this cycle. Energy consumption planning is one of the principal tasks performed within the energy planning stage. The planning of energy consumption involves establishing cause-and-effect relationships between energy-related and operational factors at the level of technological systems, infrastructure facilities, processes, and equipment. An EnB defined for a particular time period represents the planned level of energy consumption. According to the EN ISO 50001 standard [57], "EnB must be normalised to the variables that have an influence on energy consumption". The development of mathematical models describing energy consumption while considering relevant operational variables constitutes one of the principal approaches for determining the EnB.

Within UWSs, the objective of energy management is to ensure the efficient utilisation of natural resources, including water, and energy resources, primarily electricity. Within the SCE framework, energy management in UWSs should additionally support coordinated interaction between water infrastructure, manufacturing systems, logistics infrastructure, and energy subsystems through interconnected resource and information flows across SCMCs.

Electricity consumption planning requires consideration of the results of water supply planning processes within SCMCs. In this context, the dependence of technological parameters of water supply processes on water demand within SCMCs should be explicitly considered. The integration of blockchain and IoT technologies supports access to traceable and tamper-resistant historical records related to water consumption and the formation of water demand profiles [9]. These data are subsequently used for water supply planning and operational coordination processes within the SCE environment.

Technological process parameters, together with additional factors, including technical characteristics of infrastructure facilities, operating modes of UWS components, and energy efficiency indicators, are used for electricity consumption planning. The set of relevant variables influencing the EnB is determined according to the hierarchical level of the infrastructure facility for which planning is performed. Furthermore, the selected planning horizon, including hourly, daily, or other planning intervals, should also be considered. Access to the values of significant EnB variables is implemented through the blockchain-based digital platform, ensuring reliable and coordinated information exchange between distributed infrastructure facilities and computational agents participating in energy management processes within the SCE-oriented environment.

3.2.2. Formation of Significant Energy Baseline Variables

An analysis of the operational characteristics of the research object was performed to identify factors influencing energy consumption efficiency. Several water intake facilities provide UWS. Each water intake facility operates within the water distribution network supplying consumers located within a specific SCMC or several SCMCs of an urban district. Within the SCE, these water supply facilities interact with manufacturing, logistics, service, and energy infrastructure subsystems through interconnected resource and information flows, supporting the operational functioning of SCMCs and urban infrastructure systems.

A water intake facility includes water sources, first-stage pumping stations, water treatment and purification facilities, clean water reservoirs, and second-stage pumping stations. Underground aquifers (artesian wells) constitute the primary water source. First-stage pumping stations provide water abstraction and transport water through pipelines to treatment and purification facilities. Potable water is stored in clean water reservoirs. Second-stage pumping stations supply potable water to consumers through the water distribution network. Together, the water intake facility and the distribution network form the water supply system of an SCMC or urban district.

Water demand generated by consumers within one or several SCMCs determines the volume of water delivered to the distribution network by second-stage pumping stations. Water supply according to demand profiles is ensured through switching pumps with different capacities on and off. The potable water reserve stored in clean water reservoirs is maintained at a level sufficient to compensate for daily fluctuations in water demand. Variations in water demand result in changes in water storage volumes within clean water reservoirs. The rate of change in stored potable water volumes determines the required intensity of water supply to treatment facilities. The volume of water supplied to treatment facilities for replenishing clean water reserves is regulated through changes in the number of operating pumps in artesian well systems.

Consequently, pumping stations constitute the principal electricity consumers within urban water systems. It should be noted that discrepancies between the capacity of operating pumps at second-stage pumping stations and actual water consumption create excessive pressure within water distribution networks, leading to increased water losses and higher electricity consumption. The operation of low-capacity pumps or pumps equipped with higher-power electric motors may also result in additional electricity consumption during water transportation processes. The formation of a set of energy efficiency indicators, therefore, enables consideration of the operational efficiency of pumping unit scheduling and pump station management processes.

A one-day hourly interval was selected as the planning horizon for monitoring electricity consumption efficiency at the water intake facility level. The set of significant EnB variables was formed considering the selected electricity consumption planning horizon and the described operational characteristics of the research object. The daily volume of water Q_{II} pumped by second-stage pumping stations, the daily volume of water Q_I pumped by first-stage pumping stations, and energy efficiency indicators were selected as significant EnB variables.

The following coefficients are used as energy efficiency indicators for pumping stations and are calculated both for first-stage and second-stage pumping stations:

1. Pump equipment loading coefficient:

$$K_Q = \frac{Q}{\sum_{j \in J} Q_{r,j} \cdot T_{a,j}} \quad (1)$$

where K_Q is the pump equipment loading coefficient of the pumping station (respectively: K_{QI} for the first-stage pumping station and K_{QII} for the second-stage pumping station);

Q is the daily volume of water pumped by the pumping station (respectively: Q_I for the first-stage pumping station and Q_{II} for the second-stage pumping station), m^3; $Q_{r,j}$ is the rated capacity of the j-th pump, m^3/h; $T_{a,j}$ is the actual operating time of the j-th pump, h; J is the set of operating pumps; and j is the pump index.

This coefficient characterises the efficiency of pump unit capacity utilisation and enables evaluation of the correspondence between the planned water supply regime and actual water demand.

2. Electricity consumption efficiency coefficient:

$$K_P = \sum_{j \in J} \frac{P_{r,j} \cdot T_{a,j}}{Q_{a,j}} \tag{2}$$

where K_P is the electricity consumption efficiency coefficient of the pumping station (respectively: K_{PI} for the first-stage pumping station and K_{PII} for the second-stage pumping station), kWh/m^3; $Q_{a,j}$ is the actual volume of water pumped by the j-th pump, m^3; and $P_{r,j}$ is the rated power of the j-th pump motor, kW.

This coefficient characterises the efficiency of pump unit utilisation in terms of electric motor power consumption.

The electricity consumption efficiency coefficients of the pumping stations are calculated using data related to technological parameters of the water supply process, operating modes of pumping units, and parameters of operating equipment. Access of the computational agent to the required input data, as well as aggregation of calculation results, is implemented through the blockchain platform.

3.2.3. Mathematical Formulation of the Electricity Consumption Modelling Problem

The electricity consumption modelling problem is formulated as follows. Values of electricity consumption W and significant EnB variables X were obtained from N observations. The analytical relationship $W = f(X)$, which describes the relationship between the input parameters (significant energy baseline variables) and the output variable (electricity consumption), should be determined on the basis of the obtained experimental data.

The selected formulation of the modelling problem determines the structure of the mathematical model to be developed. The electricity consumption model belongs to the class of multivariate regression models and has the following form:

$$W = \sum_{m \in M} b_m \cdot g_m(X) + \varepsilon \tag{3}$$

where W is the electricity consumption, kWh; b_m are the model parameters associated with the m-th significant EnB variable; X is the set of significant EnB variables; M is the set of indices of significant EnB variables; m is the variable index; $g_m(X)$ is the m-th basis function of the input significant EnB variables; and ε is the random error term.

The random error term represents the deviation between actual and predicted values. The average absolute value of the random error term is minimised:

$$\overline{E} = \frac{1}{N} \sum_{n \in N}^{N} |\varepsilon_n| \to min \tag{4}$$

where N is the number of observations, and n is the observation index.

The random error term is assumed to have zero mean and finite variance.

3.2.4. Implementation of Structural and Parametric Model Identification

The development of a mathematical model for any process requires the determination of the model structure and estimation of its parameters. However, the structure of the electricity consumption model is unknown. The GMDH is applied to solve modelling problems under conditions of uncertainty. GMDH is an inductive modelling method based on the principles of evolutionary self-organisation of mathematical models of complex systems [58,59]. GMDH does not require prior information regarding the model type, relationships between variables, or functional dependencies. The method automatically performs structural and parametric identification of the mathematical model on the basis of experimental data. The model is constructed during algorithm execution through automatic generation and sequential selection of progressively more complex model structures [58,59].

The GMDH NN algorithm was selected for model synthesis. The GMDH NN is a self-organising neural network consisting of several layers and multiple neurons within each layer. The network structure is determined automatically during the model synthesis process. GMDH-based modelling has been applied to energy baseline and energy-consumption modelling problems, demonstrating its suitability for data-driven identification of energy-consumption relationships [60,61]. The NN training procedure is based on the evolutionary self-organisation mechanism of GMDH. A combinatorial algorithm is used to optimise neuron interconnections within the GMDH NN architecture. The organisation of combinatorial search procedures is implemented through the specification of reference functions. The multilayer GMDH NN synthesis algorithm performs model construction on the basis of multiple reference function types and sequential evaluation of the generated candidate models. The optimal model is selected according to the minimum value of external model selection criteria. The GMDH NN algorithm automatically determines significant variables, functional structure, and model parameters.

The GMDH Shell DS V3.8.9 [59] software environment was applied for machine learning implementation and structural-parametric identification of models. GMDH Shell automatically trains NN and applies them for analytical processing and forecasting tasks, enabling prediction with low error levels [59].

3.2.5. Model Validation and Selection of the Optimal Model Structure

The following classes of support functions were selected to identify the optimal structure of the mathematical model: class 1—linear; class 2—polynomial; class 3—second-degree nonlinear; class 4—second-degree polynomial; class 5—third-degree nonlinear; and class 6—third-degree polynomial. The selected support-function set covers mathematical relationships ranging from simple linear to cubic nonlinear forms, providing different levels of model complexity within the GMDH structural search. Complex polynomial functions (classes 2, 4, and 6) represent interactions among significant variables and multifactor relationships between electricity consumption, pumped water volume, and energy-efficiency indicators characterising water-supply performance. Nonlinear functions (classes 3 and 5) and complex polynomial functions (classes 2, 4, and 6) broaden the structural search space, while limiting the maximum polynomial order to three prevents unnecessary model complexity.

The data were divided into three chronological datasets: Train, Validation, and Test. Given the requirements of operational planning, the original data were partitioned chronologically without random shuffling to prevent data leakage between the datasets. The training dataset N_A was used for model construction. The testing dataset N_B was used for model testing. The control dataset N_C was used to evaluate forecasting accuracy. The control dataset was not used during model training or testing.

The GMDH algorithm estimates model coefficients using the training dataset and validates them using the testing dataset. The validation strategy determines the model verification procedure and the implementation of the external criterion for model ranking. The blocked sequential K-fold cross-validation procedure was implemented for model validation. This validation strategy involves repeated model training and validation over k iterations. At each iteration, a defined subset of data is excluded from the initial dataset and forms the testing dataset, while the remaining data form the training dataset. The training and testing datasets are generated k times. The procedure is repeated until all observations have been included in the testing dataset.

The GMDH NN algorithm identifies the optimal model within each predefined class of support functions. The model is selected from a set of candidate models through sequential selection based initially on the external regularity criterion, followed by refinement using the Criterion of Minimum Bias.

The correlation coefficient R, the coefficient of determination R^2, external regularity criterion $\Delta(B)$, and the unbiasedness criterion n_{unb} were used to evaluate model adequacy. The root mean square error (RMSE) was used to calculate of the external regularity criterion. Model regularity increases as the RMSE decreases and the coefficient of determination increases. The Criterion of Minimum Bias enables the selection of a model that is less sensitive to variations in the dataset used for parameter estimation. Application of this criterion also enables reconstruction of relationships concealed within noisy data.

Model adequacy and forecasting error $\Delta(C)$ were taken into account when selecting the best model from the obtained candidate models. The applied criteria should provide non-redundant information. Selection of the optimal model structure requires simultaneous satisfaction of the following conditions:

$$R^2 \to max;\ \Delta(B) \to min;\ n_{unb} \to min;\ \Delta(C) \to min \tag{5}$$

Criteria calculated using different datasets were considered. The coefficient of determination R^2 was calculated using the training dataset. The external regularity criterion $\Delta(B)$ was calculated using the testing dataset. The forecasting error $\Delta(C)$ was calculated using the control dataset.

Mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) were used to evaluate the approximation capability of the model and forecasting accuracy.

A multi-criteria analysis approach based on a morphological criterion was applied to select the optimal mathematical model structure [9,61]. The normalised values of criteria (5) for each model were represented using radar charts (RCs), and the corresponding chart areas were calculated. The model with the minimum RC area was selected as the optimal model.

The following section presents the results of modelling the energy consumption of the UWS within the SCMC framework, based on monitoring system data obtained from water supply enterprises in Ukraine and Poland during the period 2022–2025.

4. Results

4.1. Model Performance and Comparative Analysis

Retrospective datasets for daily electricity consumption W and daily values of significant EnB variables X_m, $m \in M$, obtained from N observations, were used as input data for the GMDH NN model synthesis algorithm. Within the proposed SCE-based digital energy management framework, the monitoring, aggregation, and analytical processing of opera-

tional data are performed through integrated information exchange between computational agents, monitoring subsystems, and decision-support components.

According to Section 3.2.2, the following variables were selected as significant EnB variables: the daily volume of water Q_{II} pumped by second-stage pumping stations; the daily volume of water Q_I pumped by first-stage pumping stations; the pump equipment loading coefficient of the second-stage pumping station K_{QII}; the electricity consumption efficiency coefficient of the second-stage pumping station K_{PII}; and the electricity consumption efficiency coefficient of the first-stage pumping station K_{PI}. Daily values of the significant EnB variables were determined using monitoring system data related to the water supply process, operating modes of pumping units, and parameters of operating equipment. The operational energy-management task in the UWS involves planning electricity consumption for the working week based on the planned operating regimes of the first- and second-stage pumping stations. The final seven observations were reserved as an independent test set for final verification of forecasting accuracy. The remaining data, representing approximately 99% of the dataset, were used for model development and structural optimisation. A five-fold sequential cross-validation procedure (K = 5) was applied to optimise the GMDH neural-network structure, iteratively select the best-performing models within each support-function class, and reduce overfitting to historical data. Within each validation fold, GMDH Shell DS V3.8.9 automatically partitioned the data into training (70%) and testing (30%) subsets. The output of the GMDH NN algorithm is the generation of a set of candidate models, each of which is optimal within a predefined class of support functions. The structure of the candidate model corresponding to a given class of support functions is presented in Appendix A.

The performance evaluation of the candidate mathematical models was carried out using the validation and selection criteria presented in Section 3.2.5. The results of model performance evaluation (Table 2) demonstrate high approximation capability and forecasting accuracy of the obtained candidate models. The evaluation results indicate that increasing the complexity of the support function improves model adequacy and forecasting capability. Excessive complication of the support function does not provide substantial improvement in model performance, while the structural complexity of the model increases significantly.

Table 2. Performance evaluation results of candidate models.

Performance Criterion	Support Function Class Number					
	1	**2**	**3**	**4**	**5**	**6**
R	0.935	0.954	0.969	0.992	0.989	0.99
R^2	0.875	0.91	0.939	0.984	0.978	0.98
$\Delta(B)$	242.147	207.68	131.266	78.377	77.25	77.935
n_{unb}	0.0365	0.0258	0.0039	0.0013	0.0012	0.0015
$MAPE(B)$	2.361	2.221	1.429	0.51	0.502	0.498
$RMSPE(B)$	3.452	3.044	1.752	0.649	0.645	0.65
$\Delta(C)$	138.17	114.83	79.98	71.633	71.721	72.311
$MAPE(C)$	1.036	0.989	0.897	0.513	0.517	0.521
$RMSPE(C)$	1.205	1.121	1.028	0.595	0.602	0.613

The analysis of the obtained results related to model adequacy and forecasting accuracy does not provide an unambiguous conclusion regarding the optimal model structure.

Within the proposed SCE-oriented analytical framework, a multi-criteria analysis of model performance incorporating a morphological criterion was applied to identify the optimal mathematical model structure. Preliminary transformation of the criteria to a unified optimisation objective was performed. For this purpose, the inverse value of the coefficient of determination was introduced:

$$Toler(R^2) = 1 - R^2 \quad (6)$$

The normalised values of each model performance criterion were calculated relative to their maximum values and are presented in Table 3.

Table 3. Results of performance criteria normalisation.

Support Function Class Number	Values of Performance Criteria				Normalised Values of Performance Criteria			
	R^2	$\Delta(B)$	n_{unb}	$\Delta(C)$	$Toler'(R^2)$	$\Delta'(B)$	n'_{unb}	$\Delta'(C)$
1	0.875	242.147	0.0365	138.17	1	1	1	1
2	0.91	207.68	0.0258	114.83	0.720	0.858	0.707	0.831
3	0.939	131.266	0.0039	79.98	0.488	0.542	0.107	0.579
4	0.984	78.377	0.0013	71.633	0.128	0.324	0.036	0.518
5	0.978	77.25	0.0012	72.311	0.176	0.319	0.033	0.523
6	0.98	77.935	0.0015	71.81	0.160	0.322	0.041	0.520

The obtained normalised values of the performance criteria were used to calculate the coordinates of the radar chart (RC) vertices corresponding to each criterion and to determine the RC area. The calculation results are presented in Table 4.

Table 4. Results of morphological criterion calculation.

Support Function Class Number	Performance Criterion								RC Area
	R^2		$\Delta(B)$		n_{unb}		$\Delta(C)$		
	RC Vertex Number Corresponding to the Criterion								
	1		2		3		4		
	Angle Corresponding to the Criterion								
	90		180		270		360		
	Coordinates of RC Vertices Corresponding to the Criterion								
	x_1	y_1	x_2	y_2	x_3	y_3	x_4	y_4	
1	0.8940	−0.4481	−0.8012	−0.5985	−0.1574	0.8800	−0.7682	0.2273	0.4559
2	0.6437	−0.3226	−0.5663	−0.4230	−0.1133	0.6336	−0.5430	0.1607	0.2320
3	0.4363	−0.2187	−0.0856	−0.0639	−0.0768	0.4295	−0.0821	0.0243	0.0238
4	0.1144	−0.0574	−0.0285	−0.0213	−0.0201	0.1126	−0.0274	0.0081	0.0021
5	0.1573	−0.0789	−0.0263	−0.0197	−0.0277	0.1549	−0.0253	0.0075	0.0026
6	0.1430	−0.0717	−0.0329	−0.0246	−0.0252	0.1408	−0.0316	0.0093	0.0030

Analysis of the morphological criterion value (the radar chart area) indicates that the best electricity consumption model among the set of candidate models is the model with the second-degree polynomial neuron activation function (class 4). This model demonstrates high forecasting capability (MAPE = 0.513% and RMSPE = 0.595%).

The results of electricity consumption modelling using the selected model are presented in Figure 2.

The confidence interval limits for the forecast values were determined on the basis of values obtained from the modelling results. The 95% confidence interval was defined as two standard deviations ($2 \cdot \sigma$) of the model residuals.

The diagram of deviations between modelled and actual electricity consumption values is presented in Figure 3. The vast majority of deviation values are located within the confidence interval limits.

The modelling results (Table 5) indicate that the deviation between actual and modelled electricity consumption values does not exceed 1%.

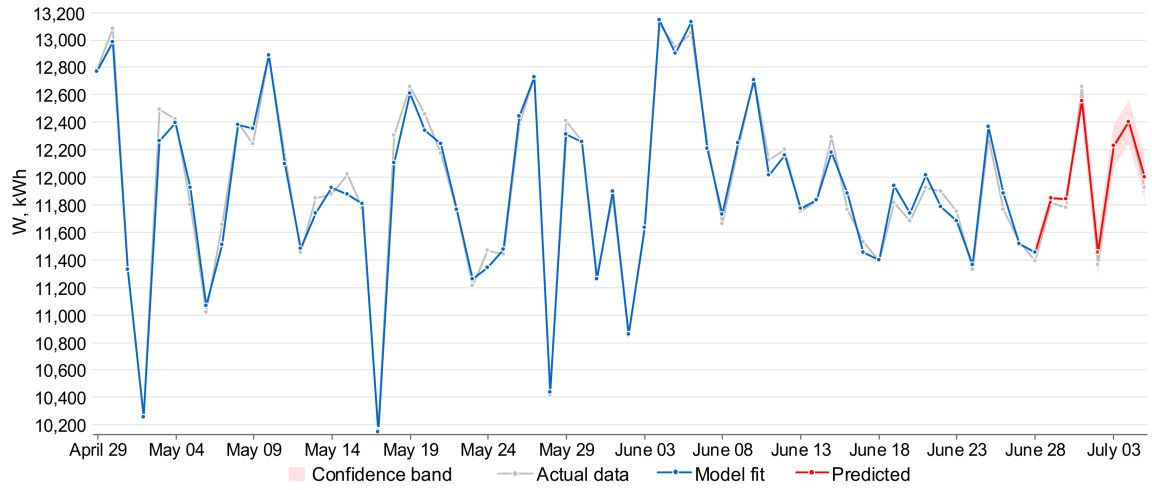


Figure 2. Fragment of a comparison of actual, approximated, and forecasted electricity consumption.

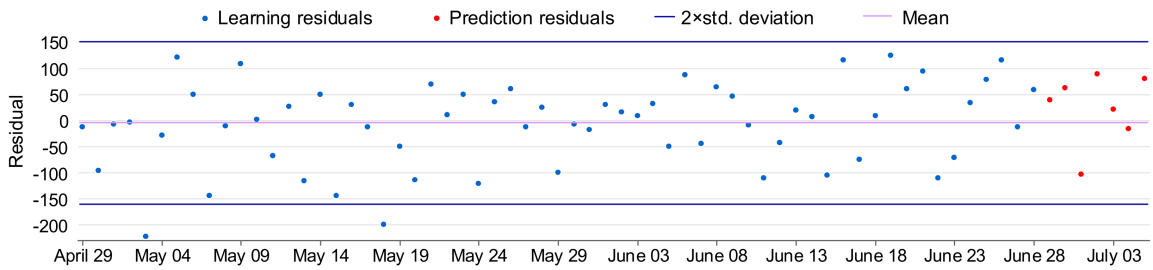


Figure 3. Fragment of deviations of modelled and actual values of power consumption.

The obtained results demonstrate the high approximation and forecasting capability of the model. The developed electricity consumption model is used to determine the EnB of the water intake facility for the following day, taking into account the results of planning technological parameters of the water supply process and operating modes of the pumping station pumps within the UWS.

Table 5. Fragment of the results of the power consumption simulation.

Data	June 22	June 23	June 24	June 25	June 26	June 27	June 28	June 29	June 30	July 01	July 02	July 03	July 04	July 05
Dataset type	Testing							Control						
Actual, kWh	11,898	11,752	11,328	12,286	11,764	11,526	11,392	11,812	11,778	12,654	11,362	12,204	12,416	11,920
Forecast, kWh	11,786.8	11,681.2	11,361.7	12,363.9	11,880.1	11,513.4	11,450.1	11,850.0	11,840.5	12,550.5	11,450.2	12,225.1	12,400.0	12,000.1
The lower limit of the forecast, kWh	11,630.1	11,524.4	11,204.9	12,207.2	11,723.2	11,356.7	11,293.2	11,693.2	11,683.8	12,393.2	11,293.2	12,068.2	12,243.2	11,843.2
The upper limit of the forecast, kWh	11,943.6	11,837.9	11,518.5	12,520.7	12,036.7	11,670.2	11,606.7	12,006.7	11,997.3	12,706.7	11,606.7	12,381.7	12,556.7	12,156.7
Deviation, kWh	−111.13	−70.81	33.75	77.96	116.10	−12.55	58.12	38.06	62.58	−103.44	88.24	21.15	−15.92	80.11
Deviation, %	−0.93	−0.60	0.30	0.63	0.99	−0.11	0.51	0.32	0.53	−0.82	0.78	0.17	−0.13	0.67

4.2. Managerial Implications

The obtained modelling results demonstrate the practical applicability of the proposed approach for energy management, operational planning, and decision support within UWSs operating in SCMCs. Within the SCE of SCMCs, the developed IAS integrates IoT-based monitoring, blockchain-supported data exchange, ML algorithms, and intelligent computational agents into a unified digital environment for coordinated management of water supply and electricity consumption processes. The proposed multi-agent architecture supports the distributed implementation of energy management tasks, including water demand forecasting, operational planning of water supply processes, optimisation of pumping station operating modes, electricity consumption planning, and adaptive operational control under dynamically changing demand conditions.

The developed electricity consumption model enables the determination of the EnB for water intake facilities based on planned technological parameters of the water supply process and operating conditions of UWS pumping stations. The achieved forecasting accuracy confirms the applicability of the proposed approach for day-ahead electricity consumption planning. It supports predictive and data-driven decision-making for load scheduling, demand-side management, and electricity procurement. This improves operational planning, reduces inefficient electricity consumption and operational costs, and increases the energy efficiency and resilience of water supply infrastructure within SCMCs. The proposed approach enables coordination of water demand forecasting, operational planning, and electricity consumption modelling across manufacturing, logistics, service, residential, and infrastructure subsystems within the SCE framework. Such coordination is particularly important under stochastic water consumption conditions and variable operating regimes of UISs. The proposed IAS architecture improves transparency, interoperability, reliability, and consistency of operational data flows between distributed infrastructure objects, computational agents, and decision-support subsystems.

Integration of blockchain and IoT technologies supports traceable data acquisition, integrity-preserving storage, and verifiable exchange of operational data required for forecasting, monitoring, and control procedures [62,63]. This reduces risks associated with incomplete or unreliable information and enables adaptive management of water supply and electricity consumption processes. Application of ML algorithms further increases the flexibility and resilience of UWS management processes through rapid adaptation of forecasting models to changing operational conditions and infrastructure loading levels. The modular, open, scalable, and reliable structure of the proposed IAS enables integration of new infrastructure objects, computational agents, and application-specific algorithms across different hierarchical levels of UWSs and other urban infrastructure facilities. Consequently, the proposed methodology may be applied not only to individual water intake facilities but also to integrated energy management systems operating within smart water grids and broader digitally transformed urban infrastructure environments.

The obtained results support the implementation of digital governance principles and sustainable development objectives within the SCE of SCMCs by supporting energy-efficient planning, resource-use monitoring, and data-driven management of urban water infrastructure. The proposed approach therefore contributes to the achievement of the SDGs, particularly SDG 6, SDG 7, SDG 9, SDG 11, and SDG 13.

5. Discussion and Conclusions

The principles of sustainable development and climate neutrality require improvements in energy efficiency and reductions in final resource consumption across all sectors of the economy [64]. In this context, the efficient utilisation of energy, water, and other natural resources within urban infrastructure systems constitutes one of the fundamen-

tal principles of sustainable urban development and an important priority for urban manufacturing systems aimed at mitigating climate change impacts. Achieving energy efficiency targets and reducing final energy consumption require the continuous development and improvement of monitoring and energy management systems within urban production environments.

UWSs constitute one of the critical life-support infrastructures of SCMCs and urban areas as a whole. Within the SCE framework, UWSs interact with manufacturing, logistics, energy, and service subsystems through interconnected resource and information flows supporting coordinated infrastructure operation across SCMCs. The objective of energy management in UWSs is to ensure the rational utilisation of energy resources, primarily electricity, and natural resources, including water, in order to improve the energy efficiency of urban water systems and ensure a sustainable water supply. The implementation of energy management tasks requires systematic monitoring, planning, and control of water supply processes, utilisation of production capacities, electricity consumption, and operation of UWS infrastructure components [65]. Data acquisition and visualisation, data analysis and forecasting, as well as optimisation and control of water supply and electricity consumption processes, constitute the principal components of efficient energy management systems. In this context, the energy management information system is considered a set of methods, analytical tools, and computational procedures supporting data acquisition, storage, processing, analysis, monitoring, control, and managerial decision-making.

The development of Industry 4.0 digital technologies and their integration into UWSs contribute to the digitalisation of water infrastructure and the formation of SWGs. Contemporary SWG development and implementation of the Water 4.0 concept involve the integration of IoT technologies, intelligent devices, and distributed sensors. IoT-based smart metering technologies provide continuous acquisition of heterogeneous operational data. This creates new opportunities for applying advanced intelligent data analytics methods and algorithms to identify hidden operational relationships, support managerial decision-making, and improve adaptive control processes within SWGs. The increasing number of IoT devices results in rapid growth in data volumes requiring analytical processing, as well as challenges related to data integrity, traceability, reliability, and secure information exchange. The performance of IoT-enabled systems also depends on the efficiency of the underlying communication infrastructure. Butt et al. [66] highlighted the importance of dynamic bandwidth assignment in TDM-based passive optical networks for efficient bandwidth utilisation and communication performance.

The proposed blockchain-integrated energy management information system architecture supports data integrity and traceability for data generated by IoT devices within the UWS infrastructure, together with distributed storage and analytical processing of operational datasets [67]. The unified information space implemented through a blockchain-based digital platform integrates all energy management subsystems, supports distributed data exchange and management, enables interaction between computational agents within the big data analytics subsystem, and ensures communication between computational agents, databases, and knowledge bases. Datasets used by computational agents, together with analytical outputs generated during modelling and forecasting procedures, are stored within the blockchain environment. Smart contract execution and consensus mechanisms are implemented both during data acquisition within IoT networks and during information exchange between computational agents. This approach supports data integrity and traceability during information exchange between IoT devices, distributed data-storage components, and computational agents involved in monitoring and control of water supply and electricity consumption processes within the SCE environment.

The complexity and hierarchical structure of UWSs determine the necessity of considering the operational characteristics of infrastructure facilities and technological water supply processes at each hierarchical level of the system. The hierarchical structure of UWSs determines the hierarchical nature of energy management problems. The stratified representation applied in this study decomposes the global energy management problem into interconnected subproblems. Each subproblem is solved according to the hierarchical level of the research object and the corresponding level of problem abstraction. This approach simplifies the representation of infrastructure facilities and facilitates the implementation of computational procedures and algorithms performed by analytical agents.

The principles of stratified representation were incorporated into the formulation of the electricity consumption planning problem at the water intake facility level. Electricity consumption planning was considered as a problem of determining the EnB while accounting for the results of water supply process planning. A mathematical model of electricity consumption was developed to determine the EnB. The set of significant EnB variables was formed considering the operational characteristics of the research object, the selected problem formulation, and the planning horizon.

The GMDH NN algorithm was selected as the machine learning method for electricity consumption model synthesis. The GMDH NN algorithm identifies relationships within datasets and automatically determines significant variables, functional structures, and model parameters. The multilayer GMDH NN synthesis algorithm constructs multiple candidate models using various activation functions, sequentially evaluates these models, and selects the optimal solution first according to the external regularity criterion and subsequently according to the unbiasedness criterion. Six classes of reference neuron activation functions were analysed to identify the most appropriate mathematical structure of the electricity consumption model. The GMDH NN algorithm determined the optimal model within each activation function class. A multi-criteria analysis approach incorporating a morphological criterion was subsequently applied to select the best mathematical model structure. Model adequacy criteria and forecasting error indicators were considered during model selection. The criteria were evaluated using different datasets to avoid duplication of assessment indicators. The optimal mathematical model was selected according to the morphological criterion represented by the area of the regularity criterion curve (RC area). The best-performing model utilised a second-order polynomial neuron activation function. The selected model demonstrated high predictive capability, achieving MAPE = 0.513% and RMSPE = 0.595%. The modelling results indicate that deviations between actual and predicted electricity consumption values do not exceed 1%. The developed electricity consumption model enables day-ahead determination of the EnB while considering planned technological parameters of the water supply process and pump operating schedules [65].

The obtained results also have practical managerial implications for energy management within SCMCs operating in the SCE environment. The developed forecasting approach may support day-ahead electricity consumption planning, optimisation of pumping station operating modes, and coordination of water supply processes with variable water demand conditions. Integration of IoT monitoring, blockchain-based data exchange, and ML models supports operational planning and adaptive management of UWS infrastructure under conditions of stochastic water consumption and dynamic operating regimes [68,69]. The proposed approach supports the sustainable and energy-efficient operation of UWSs within SCMCs. It contributes to the implementation of SDGs related to clean water, clean energy, sustainable urban infrastructure, and climate action.

UWSs are typically supplied by several water intake facilities, each characterised by specific operational features. The composition of water consumers within an SCMC or urban district, including the proportion of industrial consumers and residential popula-

tion, determines water demand levels. The volumes of water pumped by first-stage and second-stage pumping stations, together with equipment parameters and technological characteristics of water supply processes, determine the electricity consumption of individual water intake facilities. Nevertheless, the general characteristics of water supply and electricity consumption processes, as well as the principal factors influencing their efficiency, remain typical for different water intake facilities. The generalisability of the modelling results is limited by the technical, operational, and environmental conditions of the investigated UWSs. Application of the GMDH-based EnB model to other UWS configurations requires local retraining and validation. Future research should validate the proposed framework across a broader range of UWS configurations and operating conditions.

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Abbreviations

BDA	Big Data Analytics
EnB	Energy Baseline
GMDH	Group Method of Data Handling
IAS	Information and Analytical System
IoT	Internet of Things
NN	Neural Network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RC	Radar Chart
RMSE	Root Mean Square Error
RMSPE	Root Mean Square Percentage Error
SCE	Supply Chain Ecosystem
SCMC	Smart City Manufacturing Cluster
SDG	Sustainable Development Goals
SWG	Smart Water Grid
UIS	Urban Infrastructure System
UWS	Urban Water System

Appendix A. Candidate Model Structures

Table A1. Optimal Models within the Selected Classes of Reference Neuron Activation Functions.

Reference Function Class Number	Mathematical Model Structure
1	$Y1 = 2644.07 + N26 \times 1.10602 + N46 \times 0.998501 - N136 \times 0.340462$ $N26 = -4387.74 + N108 \times 1.02929 + N159 \times 1.46596 - N188 \times 0.48022$ $N108 = 11{,}339.3 + Q_{II} \times 0.221358 - K_{IIQ} \times 7404.32$ $N159 = 1269.17 + Q_{II} \times 0.234717 + K_{IIP} \times 11{,}773.2$ $N188 = 1932.43 + Q_{II} \times 0.228786 + K_{IP} \times 10{,}687.8$ $N46 = -12{,}855.5 + N180 \times 1.02142 + N215 \times 1.11333$ $N180 = 5144.36 + Q_{II} \times 0.245753 - Q_{I} \times 0.0214002$ $N215 = 14{,}107.9 + K_{IIP} \times 7036.32 - K_{IIQ} \times 5471.33$ $N136 = -6030.06 + N142 \times 0.882205 + N155 \times 0.65246$ $N142 = 17{,}087.2 + Q_{I} \times 3.1984 \times 10^{-3} - K_{IIQ} \times 8216.06$ $N155 = 7672.87 + Q_{I} \times 1.772 \times 10^{-3} + K_{IP} \times 10{,}908$
2	$Y1 = 35440.3 + N10 \times N15 \times 0.0272212 - N15 \times 5.21885$ $N15 = 2436.92 + N34 \times N26 \times 6.92556 \times 10^{-3}$ $N26 = -2.98225 + N31 \times N36 \times 8.82925 \times 10^{-3}$ $N36 = 84{,}120.9 - N47 \times 7.49498 + N47 \times N28 \times 6.375 \times 10^{-3} - N28 \times 6.15566$ $N28 = -97{,}223.6 + N44 \times 8.64321 - N44 \times N22 \times 7.13415 \times 10^{-3} + N22 \times 9.02439$ $N47 = 43{,}545.4 - Q_{I} \times 0.807009 + Q_{I} \times K_{IP} \times 3.11096 - K_{IP} \times 124{,}320$ $N44 = 49{,}746.1 - Q_{I} \times 0.972172 + Q_{I} \times K_{IIP} \times 3.49362 - K_{IIP} \times 138{,}113$ $N22 = 113.84 + N37 \times N42 \times 8.73814 \times 10^{-3}$ $N42 = 88{,}223.3 - K_{IIP} \times 258{,}002 + K_{IIP} \times K_{IIQ} \times 302{,}900 - K_{IIQ} \times 90{,}159.4$ $N37 = 12{,}226.7 + Q_{II} \times Q_{I} \times 6.00229 \times 10^{-4} - Q_{I} \times 0.195011$ $N31 = 4650.9 + Q_{II} \times 0.115337 + Q_{II} \times K_{IIP} \times 0.415959$ $N10 = 509.714 + N20 \times N38 \times 8.42931 \times 10^{-3}$ $N38 = 502{,}347 - N39 \times 42.4906 + N39 \times N43 \times 0.0393798 - N43 \times 45.4694$ $N43 = 9028.67 + K_{IP} \times 8745.65$ $N39 = -459.106 + K_{IP} \times 38{,}964.1 - K_{IP} \times K_{IIP} \times 129{,}333 + K_{IIP} \times 3959.9$ $N20 = 1783.61 + N30 \times N34 \times 7.43547 \times 10^{-3}$ $N34 = 88{,}223.3 - K_{IIP} \times 258{,}002 + K_{IIP} \times K_{IIQ} \times 302{,}900 - K_{IIQ} \times 90{,}159.4$ $N30 = 16{,}786.2 + Q_{II} \times K_{IIQ} \times 0.262011 - K_{IIQ} \times 13{,}823.8$
3	$Y1 = 7084.06 - N17 \times 0.232612 + N2^2 \times 5.34261 \times 10^{-3}$ $N2 = 1542.14 - N41 \times 0.170598 + N5 \times 1.03447$ $N5 = 2607.3 - N22 \times 11.6688 + N22^2 \times 5.2461 \times 10^{-3} + N8 \times 12.3157 - N8^2 \times 0.0513577$ $N8 = -14{,}047.1 - K_{IIP} \times 162{,}217 + K_{IIP}{}^2 \times 268{,}178 + N17 \times 7.53796 - N17^2 \times 0.0277188$ $N22 = -22{,}279.6 + N25 \times 4.75787 - N25^2 \times 0.0181614 + N32^2 \times 2.3909 \times 10^{-3}$ $N32 = -371{,}917 + N40^2 \times 4.2054 \times 10^{-4} + N46 \times 66.0837 - N46^2 \times 2.888 \times 10^{-3}$ $N46 = 36{,}100.9 - K_{IP} \times 158{,}976 + K_{IP}{}^2 \times 319{,}750 - K_{IIQ} \times 5912.44$ $N25 = -4939.67 + N39^2 \times 4.26065 \times 10^{-3} + N43 \times 0.952413$ $N39 = 8647.36 + Q_{II}{}^2 \times 4.21598 \times 10^{-3} - Q_{I} \times 0.0199918$ $N41 = 2612.15 + N44^2 \times 3.78902 \times 10^{-3} + N47 \times 0.339923$ $N44 = -98{,}965.6 + Q_{II}{}^2 \times 5.09388 \times 10^{-3} + K_{IIQ} \times 258{,}971 - K_{IIQ}{}^2 \times 152{,}953$ $N17 = 148{,}663 + N30 \times 0.968736 - N45 \times 27.5595 + N45^2 \times 0.0127644$ $N45 = -441{,}793 + N47 \times 79.2554 - N47^2 \times 0.0346419$ $N47 = 11{,}748.3 + K_{IIP} \times 7016.64 - K_{IIQ}{}^2 \times 3160.39$ $N30 = -123{,}004 + N40^2 \times 4.23186 \times 10^{-3} + N43 \times 22.1204 - N43^2 \times 0.0947615$ $N43 = -7051.27 - K_{IP} \times 967{,}507 + K_{IP}{}^2 \times 1.82708 \times 10^{3} + K_{IIP} \times 10{,}260.4 - K_{IIP}{}^2 \times 17{,}955$ $N40 = 28{,}480.5 + Q_{I}{}^2 \times 3.97861 \times 10^{-3} - K_{IP} \times 167{,}496 + K_{IP}{}^2 \times 340{,}081$

Table A1. *Cont.*

Reference Function Class Number	Mathematical Model Structure
4	$Y1 = 88{,}807.1 - N40 \times 18.8561 - N40 \times N2 \times 4.06067 \times 10^{-3} + N40^2 \times 0.0104678 + N2 \times 3.90744 + N2^2 \times 7.4457 \times 10^{-4}$ $N2 = 6082.59 - N8 \times N4 \times 7.70896 + N4 \times 2.7396 + N8^2 \times N4^2 \times 0.01104216$ $N8 = 23{,}318.9 - Q_I \times 1.14553 + Q_I \times K_{IP} \times 2.91445 + Q_I^2 \times 9.26326 \times 10^{-5} - K_{IP}^2 \times 129{,}968$ $N4 = -948.148 + N11 \times N14 \times 4.82678 \times 10^{-3} - N11^2 \times 2.38718 \times 10^{-3} + N14 \times 1.14973 - N14^2 \times 2.44406 \times 10^{-3}$ $N14 = -7676.39 - N29 \times 5.97043 + N29 \times N18 \times 6.60725 \times 10^{-3} - N29^2 \times 3.05514 \times 10^{-3} + N18 \times 8.35723 - N18^2 \times 3.61356 \times 10^{-3}$ $N18 = -55{,}750.8 - N42 \times N34 \times 8.04608 \times 10^{-3} + N42^2 \times 4.3637 \times 10^{-3} + N34 \times 10.0916$ $N34 = -900{,}303 + N38 \times 4.84327 - N38 \times N46 \times 3.32086 \times 10^{-3} + N46 \times 154.154 - N46^2 \times 0.0659845$ $N38 = 28{,}480.5 + Q_{II}^2 \times 3.97861 \times 10^{-4} - K_{IP} \times 167{,}496 + K_{IP}^2 \times 340{,}081$ $N42 = 109{,}982 - K_{IP} \times 436{,}420 + K_{IP} \times K_{IIQ} \times 328{,}782 + K_{IP}^2 \times 300{,}537 - K_{IIQ} \times 91{,}891.4$ $N29 = -360{,}453 + N36 \times 3.45374 + N36 \times N47 \times 1.38143 \times 10^{-3} - N36^2 \times 1.71997 \times 10^{-3} + N47 \times 59.5004 - N47^2 \times 2.62562 \times 10^{-3}$ $N47 = 23{,}974.1 - K_{IP} \times 105{,}999 + K_{IP}^2 \times 219{,}641$ $N36 = 16{,}262.4 - Q_{II} \times 0.381121 - Q_{II} \times K_{IIQ} \times 0.211558 + Q_{II}^2 \times 1.35973 \times 10^{-5}$ $N11 = -699.932 + N39 \times 1.81637 + N39 \times N22 \times 4.74671 \times 10^{-3} - N39^2 \times 2.44017 \times 10^{-3} - N22 \times 0.685256 - N22^2 \times 2.31099 \times 10^{-3}$ $N22 = 52{,}588.2 - K_{IIQ} \times 60{,}378.4 + K_{IIQ} \times N33 \times 4.81827 - N33 \times 3.19767$ $N33 = -857{,}961 + N39 \times 8.79327 - N39^2 \times 3.32161 \times 10^{-3} + N46 \times 141.535 - N46^2 \times 6.16254 \times 10^{-3}$ $N46 = 22{,}854.9 - K_{IP} \times 98{,}319.2 + K_{IP} \times K_{IIP} \times 4.36333 \times 10^6 - K_{IP}^2 \times 212{,}255 - K_{IIP}^2 \times 2{,}042{,}486$ $N39 = 16{,}557.4 - Q_{II} \times 0.582844 + Q_{II}^2 \times 1.3862 \times 10^{-4}$ $N40 = 48{,}091.7 - N43 \times N48 \times 1.46967 \times 10^{-3} + N43^2 \times 7.8961 \times 10^{-3} - N48 \times 7.78998 + N48^2 \times 0.0108082$ $N48 = 9101.22 + K_{IIP} \times 7938.97$ $N43 = 12{,}570.6 + K_{IIP} \times K_{IIQ} \times 327{,}821 - K_{IIP}^2 \times 498{,}407 - K_{IIQ}^2 \times 55{,}299.4$
5	$Y1 = 18{,}766.9 - N9 \times 4.25064 + N9^2 \times 0.0443273 - N9^3 \times 1.46974 \times 10^{-4} + N2^2 \times 4.05114 \times 10^{-3}$ $N2 = 46{,}067.5 + N4 \times 15.2666 + N4^2 \times 3.05474 \times 10^{-3} - N4^3 \times 3.77054 \times 10^{-4} - N5 \times 26.9786 + N5^2 \times 0.0113505 + N5^3 \times 2.19594 \times 10^{-4}$ $N5 = 217{,}789 - N25 \times 141.533 + N25^2 \times 0.0117967 - N25^3 \times 3.24318 \times 10^{-3} + N10 \times 89.381 - N10^2 \times 0.0748836 + N10^3 \times 2.08343 \times 10^{-4}$ $N4 = 102{,}910 - N33 \times 442.394 + N33^2 \times 0.0388333 - N33^3 \times 1.13391 \times 10^{-3} + N10 \times 176.632 - N10^2 \times 0.0158097 + N10^3 \times 4.72328 \times 10^{-4}$ $N10 = 390{,}182 - N29 \times 195.776 + N29^2 \times 0.0163719 - N29^3 \times 4.53766 \times 10^{-4} + N18 \times 96.1846 - N18^2 \times 0.0773755 + N18^3 \times 2.07029 \times 10^{-4}$ $N18 = 1{,}663{,}107 - N46 \times 4429.73 + N46^2 \times 0.398194 - N46^3 \times 1.19248 \times 10^{-5} - N29 \times 55.7339 + N29^2 \times 0.0500631 - N29^3 \times 1.47045 \times 10^{-4}$ $N29 = -10{,}236.4 + N41 \times 0.975975 + N44 \times 0.927587$ $N41 = 142{,}380 - Q_{II} \times 13.7314 + Q_{II}^2 \times 4.69709 \times 10^{-3} - Q_{II}^3 \times 5.22603 \times 10^{-5} - Q_I^2 \times 2.3111 \times 10^{-4}$ $N9 = -74{,}058.7 + N16 \times 13.4527 - N16^2 \times 0.0562281 + N25 \times 7.52238 - N25^2 \times 0.0122671 + N25^3 \times 5.32207 \times 10^{-4}$ $N25 = 630{,}457 - N49 \times 1.20657 - N33 \times 161.165 + N33^2 \times 0.0141722 - N33^3 \times 4.1167 \times 10^{-3}$ $N33 = -18{,}261.5 + N40 \times 2.76026 - N40^2 \times 7.92198 \times 10^{-5} + N44 \times 0.751039$ $N40 = 125{,}458 - Q_{II} \times 12.2645 + Q_{II}^2 \times 0.0420096 - Q_{II}^3 \times 4.67651 \times 10^{-9} + K_{IP} \times 8752.67$ $N49 = 8926.98 + Q_I^3 \times 4.4204 \times 10^{-5} + K_{IP} \times 7875.32$ $N16 = 188{,}697 - N46 \times 4975.17 + N46^2 \times 0.447113 - N46^3 \times 1.33865 \times 10^{-3} - N32 \times 112.126 + N32^2 \times 0.0997942 - N32^3 \times 2.92922 \times 10^{-5}$ $N32 = 118{,}378 - Q_{II} \times 12.2781 + Q_{II}^2 \times 0.0419101 - Q_{II}^3 \times 4.65241 \times 10^{-5} + N44 \times 0.884259$ $N44 = -42{,}734 - K_{IP}^2 \times 1{,}856{,}236 + K_{IP}^3 \times 4{,}663{,}406 + K_{IIP} \times 512{,}501 - K_{IIP}^3 \times 2{,}087{,}336$ $N46 = 127{,}054 - K_{IIP} \times 315{,}994 + K_{IIP}^2 \times 1{,}162{,}335 - K_{IIP}^3 \times 141{,}762 - K_{IIQ} \times 342{,}559 + K_{IIQ}^2 \times 401{,}483 - K_{IIQ}^3 \times 1{,}568{,}595$

Table A1. *Cont.*

Reference Function Class Number	Mathematical Model Structure
6	$Y1 = 94{,}645.2 - N14 \times N2^2 \times 1.22293 \times 10^{-6} + N14^2 \times 1.11835 \times 10^{-3} + N14^2 \times N2 \times 1.11363 \times 10^{-4} - N14^3 \times 4.58657 \times 10^{-5} + N14^3 \times N2 \times 5.20955 \times 10^{-6} - N2 \times 32.0743 + N2^2 \times 3.17093 \times 10^{-3} + N2^3 \times 3.22923 \times 10^{-6}$ $N2 = -76{,}393.3 + N7 \times 24.2495 - N7 \times N3^2 \times 1.11943 \times 10^{-5} + N7 \times N3^3 \times 5.8417 \times 10^{-7} - N7^2 \times 3.28234 \times 10^{-3} + N7^2 \times N3 \times 3.43086 \times 10^{-5} - N7^2 \times N3^2 \times 1.10525 \times 10^{-6} + N3 \times 4.75438 - N3^2 \times 5.43967 \times 10^{-3}$ $N3 = 35{,}017.1 + N8 \times N4 \times 0.0194799 - N8 \times N4^2 \times 7.83466 \times 10^{-4} - N8 \times N4^3 \times 1.3471 \times 10^{-5} - N8^2 \times 7.6254 \times 10^{-3} + N8^3 \times N4 \times 1.6469 \times 10^{-6} - N4 \times 12.6789 - N4^2 \times 9.87152 \times 10^{-3} + N4^3 \times 6.56998 \times 10^{-5}$ $N4 = -23{,}759 + N42 \times 4.58401 - N42 \times N5^3 \times 1.93576 \times 10^{-6} - N42^2 \times N5 \times 5.39892 \times 10^{-5} + N42^2 \times N5^2 \times 4.08249 \times 10^{-6} + N5^2 \times 2.0472 \times 10^{-3}$ $N5 = -2{,}631{,}246 + N31 \times 1284.14 - N31 \times N6^2 \times 9.81708 \times 10^{-5} - N31^2 \times 0.169567 + N31^2 \times N6 \times 9.82359 \times 10^{-4} + N31^2 \times N6^2 \times 4.3021 \times 10^{-6} + N31^3 \times 6.65265 \times 10^{-4} - N31^3 \times N6 \times 5.76792 \times 10^{-6} - N6 \times 370.956 + N6^2 \times 0.0512274 + N6^3 \times 1.49573 \times 10^{-4}$ $N6 = -54{,}498.2 + N47 \times N8 \times 0.0283568 + N47 \times N8^3 \times 2.27207 \times 10^{-5} + N47^2 \times 8.66667 \times 10^{-3} - N47^2 \times N8^2 \times 5.45601 \times 10^{-6} - N47^3 \times 2.52963 \times 10^{-4} + N47^3 \times N8 \times 3.93973 \times 10^{-6} - N8^2 \times 0.0129303$ $N31 = 2{,}092{,}777 - K_{IP} \times 8{,}123{,}527 + K_{IP} \times N39 \times 20{,}395 - KIP \times N39^2 \times 1.76542 + K_{IP} \times N39^3 \times 5.1237 \times 10^{-4} + K_{IP}^2 \times 788{,}762 - K_{IP}^3 \times N39 \times 794.573 - N39 \times 5379.4 + N39^2 \times 0.467215 - N39^3 \times 1.35655 \times 10^{-4}$ $N42 = 106{,}174 + Q_{II} \times 21.0299 - Q_{II} \times K_{IIP} \times 298.135 + Q_{II} \times K_{IIP}^2 \times 943.395 - Q_{II} \times K_{IIP}^3 \times 1193.14 + Q_{II}^2 \times K_{IIP} \times 1.81152 \times 10^{-3} - Q_{II}^3 \times K_{IIP} \times 2.03986 \times 10^{-5} + K_{IIP}^3 \times 198454$ $N7 = 240{,}586 - Q_{II} \times 16.6535 + Q_{II} \times N8 \times 4.54905 \times 10^{-3} - Q_{II} \times N8^2 \times 3.6543 \times 10^{-5} + Q_{II} \times N8^3 \times 7.97419 \times 10^{-6} - Q_{II}^3 \times 1.54573 \times 10^{-5} + Q_{II}^3 \times N8 \times 1.55558 \times 10^{-6} - N8 \times 55.1601 + N8^2 \times 0.0313798$ $N8 = 117{,}142 - N15 \times 634.226 + N15 \times N16 \times 0.728706 - N15 \times N16^2 \times 3.10695 \times 10^{-4} - N15 \times N16^3 \times 2.83074 \times 10^{-5} - N15^2 \times 0.283264 - N15^2 \times N16 \times 3.13194 \times 10^{-5} + N15^2 \times N16^2 \times 5.29464 \times 10^{-6} + N15^3 \times 2.66346 \times 10^{-4} - N15^3 \times N16 \times 2.45557 \times 10^{-6} + N16 \times 593.872 - N16^2 \times 0.43979 + N16^3 \times 3.54027 \times 10^{-4}$ $N16 = 77{,}412.9 + N27 \times N30 \times 0.0312214 - N27 \times N30^2 \times 1.11732 \times 10^{-4} - N27^2 \times 0.0109627 + N27^2 \times N30 \times 1.12462 \times 10^{-4} - N27^3 \times 3.79776 \times 10^{-6} - N30 \times 20.7453 + N30^3 \times 3.66231 \times 10^{-4}$ $N30 = 4{,}342{,}037 - N51 \times 2457.97 + N51 \times N39 \times 1.1824 - N51 \times N39^2 \times 1.04404 \times 10^{-3} + N51 \times N39^3 \times 3.06535 \times 10^{-5} - N51^2 \times 0.175207 + N51^3 \times 5.12674 \times 10^{-4} - N39 \times 13{,}538 + N39^2 \times 1.19545 - N39^3 \times 3.50987 \times 10^{-5}$ $N39 = -168{,}454 + Q_{II} \times 238.687 - Q_{II} \times N50 \times 0.0753787 - Q_{II} \times N50^3 \times 1.092 \times 10^{-6} - Q_{II}^2 \times 9.76498 \times 10^{-3} + Q_{II}^2 \times N50^2 \times 7.74845 \times 10^{-6} + Q_{II}^3 \times 2.30719 \times 10^{-4} - Q_{II}^3 \times N50 \times 2.05313 \times 10^{-6} + N50^3 \times 1.20339 \times 10^{-4}$ $N27 = -1{,}071{,}777 + N33 \times 2702.86 - N33 \times N37 \times 0.250122 - N33^2 \times 0.226631 + N33^2 \times N37 \times 2.09723 \times 10^{-5} + N33^3 \times 6.32527 \times 10^{-4} - N33^3 \times N37 \times 5.85111 \times 10^{-6} + N37 \times 992.541$ $N37 = -519{,}887 + N43 \times N51^2 \times 8.63923 \times 10^{-5} - N43^2 \times N51 \times 8.22392 \times 10^{-5} + N43^3 \times 3.05491 \times 10^{-5} - N43^3 \times N51 \times 3.78114 \times 10^{-6} + N51 \times 125.484 - N51^2 \times 0.0103824$ $N43 = 45{,}280.2 - Q_{II} \times K_{IIQ} \times 11.4673 - Q_{II} \times K_{IIQ}^3 \times 1.03141 + Q_{II}^2 \times K_{IIQ} \times 4.15985 \times 10^{-3} - Q_{II}^3 \times K_{IIQ} \times 4.57603 \times 10^{-5} + K_{IIQ}^2 \times 89{,}542.5$ $N15 = -124{,}207 + N20 \times N29^2 \times 1.3526 \times 10^{-4} - N20 \times N29^3 \times 1.05874 \times 10^{-5} - N20^2 \times 0.0174559 - N20^3 \times 2.50436 \times 10^{-4} + N20^3 \times N29 \times 2.6834 \times 10^{-5} + N29 \times 447.255 - N29^2 \times 0.058134 + N29^3 \times 2.45608 \times 10^{-5}$ $N20 = -32{,}239.2 + N36 \times N41^3 \times 4.32459 \times 10^{-5} - N36^2 \times 3.37293 \times 10^{-3} - N36^2 \times N41^2 \times 1.81144 \times 10^{-5} + N36^3 \times 4.0031 \times 10^{-5} - N36^3 \times N41 \times 1.99951 \times 10^{-4} + N41^2 \times 4.94983 \times 10^{-3} - N41^3 \times 5.6771 \times 10^{-5}$ $N41 = 815{,}140 + N48 \times N51 \times 4.42771 \times 10^{-3} - N48^2 \times 0.0340213 + N48^2 \times N51 \times 2.57714 \times 10^{-4} + N48^3 \times 2.0966 \times 10^{-6} - N48^3 \times N51 \times 1.71229 \times 10^{-6} - N51^2 \times 0.0113586 + N51^3 \times 3.2813 \times 10^{-5}$ $N48 = -42{,}914.6 + Q_{II} \times 0.526892 + Q_{II} \times K_{IIQ} \times 6.13839 - Q_{II}^2 \times K_{IIQ} \times 1.75031 \times 10^{-3} + Q_{II}^3 \times K_{IIQ} \times 1.49796 \times 10^{-5} - K_{IIQ}^3 \times 30{,}773.5$ $N36 = 603{,}418 - K_{IIP} \times 9{,}301{,}527 + K_{IIP} \times N47^2 \times 0.745321 + K_{IIP}^2 \times 46{,}919{,}708 - K_{IIP}^2 \times N47 \times 25{,}595.1 - K_{IIP}^2 \times N47^2 \times 1.47031 - K_{IIP}^3 \times 76{,}404{,}908 + K_{IIP}^3 \times N47 \times 68{,}452.3 + N47 \times 504.422 - N47^2 \times 0.0933871$

Table A1. *Cont.*

Reference Function Class Number	Mathematical Model Structure
	$N14 = -1{,}507{,}056 + N26 \times N29 \times 0.010908 - N26 \times N29^3 \times 2.28596 \times 10^{-6} + N26^2 \times N29^2 \times 1.42585 \times 10^{-6} - N26^3 \times 6.23331 \times 10^{-5} + N26^3 \times N29 \times 8.01332 \times 10^{-6} + N29 \times 515.9 - N29^2 \times 0.076571 + N29^3 \times 4.3276 \times 10^{-4}$ $N29 = 3{,}849{,}226 - K_{IIQ} \times 1{,}857{,}667 - K_{IIQ} \times N33 \times 3090.56 + K_{IIQ} \times N33^2 \times 0.280313 + K_{IIQ} \times N33^3 \times 1.59288 \times 10^{-4} + K_{IIQ}^2 \times 5{,}455{,}817 - K_{IIQ}^2 \times N33^2 \times 0.475695 - K_{IIQ}^3 \times 4{,}408{,}070 + K_{IIQ}^3 \times N33 \times 4114.53 + N33^2 \times 0.113751 - N33^3 \times 1.37663 \times 10^{-5}$ $N33 = 4.87234 \times 10^7 - N44 \times 12{,}675.8 + N44 \times N50 \times 1.12189 + N44^2 \times 1.09746 - N44^2 \times N50 \times 9.70948 \times 10^{-4} - N44^3 \times 3.16201 \times 10^{-5} + N44^3 \times N50 \times 2.79661 \times 10^{-5} - N50 \times 4313.33$ $N50 = 196{,}007 - K_{IIP} \times K_{IIQ} \times 8{,}342{,}246 + K_{IIP}^2 \times 6{,}131{,}856 + K_{IIP}^2 \times K_{IIQ} \times 31{,}011{,}807 - K_{IIP}^2 \times K_{IIQ}^2 \times 8{,}773{,}060 - K_{IIP}^3 \times 32{,}060{,}607 + K_{IIQ}^2 \times 628{,}940$ $N44 = 317{,}789 - Q_I \times K_{IP} \times 288.827 + Q_I \times K_{IP}^2 \times 1284.95 - Q_I \times K_{IP}^3 \times 1511 + Q_I^2 \times 5.96417 \times 10^{-3} - Q_I^2 \times K_{IP} \times 4.01075 \times 10^{-3} - Q_I^3 \times K_{IP} \times 2.0472 \times 10^{-5} - K_{IP}^2 \times 2{,}393{,}426$ $N26 = -4{,}343{,}966 + N51 \times 1139.02 - N51^2 \times 0.0993429 - N51^2 \times N32 \times 8.58866 \times 10^{-6} + N51^3 \times 2.89506 \times 10^{-6} + N51^3 \times N32 \times 4.32402 \times 10^{-6} + N32^2 \times 5.65948 \times 10^{-3} - N32^3 \times 1.84248 \times 10^{-5}$ $N32 = -734{,}208 + N47 \times 368.411 - N47 \times N54^3 \times 1.19727 \times 10^{-6} - N47^2 \times 0.0618651 + N47^2 \times N54^2 \times 3.50218 \times 10^{-5} + N47^3 \times 4.34481 \times 10^{-4} - N47^3 \times N54 \times 3.40096 \times 10^{-6}$ $N54 = 24{,}394.1 - K_{IIP} \times K_{IIQ}^2 \times 6{,}006{,}846 + K_{IIP} \times K_{IIQ}^3 \times 212{,}539 + K_{IIP}^2 \times K_{IIQ} \times 19{,}663{,}707 - K_{IIP}^3 \times 22{,}022{,}607 + K_{IIQ}^3 \times 551{,}548$ $N47 = -9267.15 - Q_{II} \times Q_I \times 5.53915 \times 10^{-3} - Q_{II} \times Q_I^3 \times 2.16267 \times 10^{-7} + Q_{II}^2 \times 4.11842 \times 10^{-4} + Q_{II}^2 \times QI \times 1.70519 \times 10^{-6} + Q_{II}^2 \times Q_I^2 \times 1.56536 \times 10^{-5} - Q_{II}^3 \times Q_I \times 2.05789 \times 10^{-5} + Q_I \times 5.96252$ $N51 = 126{,}883 - K_{IP} \times 913{,}763 + K_{IP}^2 \times 51{,}308{,}407 - K_{IP}^2 \times K_{IP} \times 2{,}195{,}667 - K_{IP}^3 \times K_{IP} \times 1.868826$

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