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Urban water resource management for sustainable environment planning using artificial intelligence techniques

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ABSTRACT

In the current era, water is a significant resource for socio-economic growth and the protection of healthy environments. Properly controlled water resources are considered a vital part of development, which reduces poverty and equity. Conventional Water system Management maximizes the existing water flows available to satisfy all competing demands, including on-site water and groundwater. Therefore, Climatic change would intensify the specific challenges in water resource management by contributing to uncertainty. Sustainable water resources management is an essential process for ensuring the earth's life and the future. Nonlinear effects, stochastic dynamics, and hydraulic constraints are challenging in ecological planning for sustainable water development. In this paper, Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP) has been proposed to sustain the urban areas' water environment. Here, an adaptive intelligent approach is a subset of the Artificial Intelligence (AI) technique in which environmental planning for sustainable water development has been modeled effectively. Artificial intelligence modeling improves water efficiency by transforming information into a leaner process, improving decision-making based on data-driven by combining numeric AI tools and human intellectual skills. In AIDWRP, Markov Decision Process (MDP) discusses the dynamic water resource management issue with annual use and released locational constraints that develop sensitivity-driven methods to optimize several efficient environmental planning and management policies. Consequently, there is a specific relief from the engagement of supply and demand for water resources, and substantial improvements in local economic efficiency have been simulated with numerical outcomes.

1. Outline of the research

Sustainable water resources management is designed and managed to preserve their ecological, economic, and hydrological integrity of the present society and the future prespectives (Ali et al., 2019). Artificial intelligence methods have been applied in urban water resource planning primarily because of their powerful capacity for reasoning, flexibility, modeling, and predicting the water demand and capacity. Water resources are considered a significant factor in economic and social growth for effective environmental management and planning. Water resources must be appropriately allocated, utilized to assess the environment's impact, and poses a specific challenge in designing ecological systems (Lin et al., 2019; Macias-Fauria et al., 2020; Li et al., 2019a). The increasing water demand is due to climatic change, urbanization, and population growth, which need to be managed effectively for the diversified and complex urban water resources using modern technology platforms (Mrówczyńska et al., 2019; Liu et al., 2019). As technological solutions contributing to the development of a sustainable environment may allow progressive socioeconomic changes for environmental sustainability (Cazorla-Montero et al., 2019; Bazan-Krzywoszańska et al., 2019). These traditionally established technical approaches for water management and sustainable practice often reflect standard water governance (How et al., 2020). The Sustainability Index (SI) analyses the efficiency of different water policies and the environment and the system's capacity to reduce its vulnerability using artificial intelligent techniques (Prabakaran et al., 2019; Wang et al., 2019). The

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index shows that the system has a higher adaptive capacity for a suggested policy that makes the system more ecological effective (Goralski and Tan, 2020). The sustainability index integrates performance standards that capture the basin's important and long-awaited sustainabilities (Cernev and Fenner, 2020) for environment management using AI (Zhang et al., 2019). The index allows it more comfortable to compare policies as the performance criteria for effective environmental planning and management (Qian et al., 2019; Sachs et al., 2019). Fig. 1 shows the sustainable water resource management and its impacts.

As inferred from Fig. 1. The current water availability needs an effective resource management solution to satisfy the supply and demand ratio based on the food cycle. The water demand is rising, and the river basin's water management challenges exceeded their carrying ability, contributing to clear inconsistencies between supply and demand due to climatic changes (Abdo and Zeadally, 2020). Local water conservation aims at creating resilience in towns and cities that are living, efficient, and safe. Evaluation of sustainable water resources management requires responsibility for the actual overhead expense of water management. Water resources management has to be responsible. Socio-economic and environmental dimensions that are also not readily expressed in the quantitative principles needed for comprehensive planning, decision making, monitoring, and assessment Evaluation models include potential environmental sustainability metrics, which are used in comparing management strategies in different organizations and ecosystems for site modeling analyses to help individual administrators and policymakers to measure progress towards sustainable practices. Sustainable economic and environmental development has severely impacted underground water overexploitation (Di Baldassarre et al., 2019). There are many reasons why most of them are not valid due to improper unified water resource management because of the excessive water consumption and waste of water (Hameed, 2019). It allows a severe inconsistency between supply and demand (Aina et al., 2019). The study on the rational use of water resources became necessary, optimized using several intelligent planning methods (Lozano et al., 2019). Integrated Water Resources Management is a procedure that endorses integrated land (Li et al., 2019b), water, and interrelated resources development and management to optimize social and economic conditions for the sustainable (Dogo et al., 2019), dynamic ecosystems management in the future (Voronkova et al., 2019). Integrated water resources management focuses on encouraging coordination and integration to improve the water resources' sustainably (Dunets et al., 2019).

In this paper, the Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP) has been considered a subset of AI proposed for sustainable water management in urban areas. A stochastic approach to

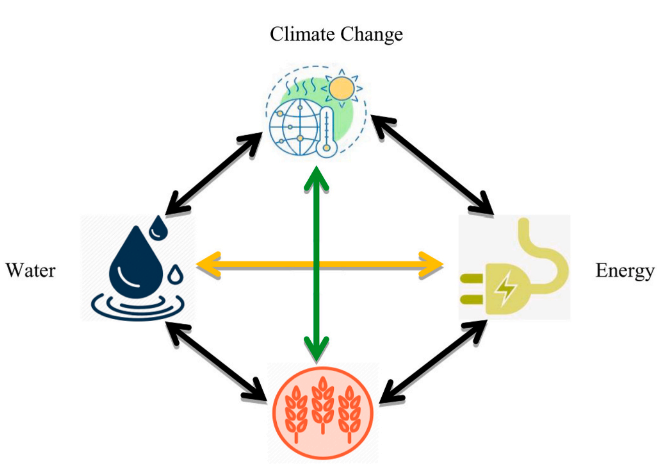

Fig. 1. Sustainable water resource management.

model the water network is designed using Markov Decision Processes to optimize the system's resource distribution in compliance with the multiple uncertainties. The Markov chain described the serial correlation for optimizing the water framework using artificial intelligence techniques, which has been integrated into AIDWRP. This research shows a method for optimizing limited basin water resources for effective environmental management and planning. This study's key objective is to develop an artificial intelligence modeling framework for water resource management to increase water resource management efficiency. Optimal water allocation is formulated using artificial intelligence to minimize costs, subjected to improved sustainable environment management. Cost savings often mark users and optimum control, described as the reservoir activity, to reduce total costs.

The significant contributions of the study are listed as follows,

- Design and develop an Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP), the subset of AI for sustainable water resource management in urban regions.
- Designing the statistical model for seasonal water demands, locational release constraints, and annual consumption constraints.
- Simulative analysis has been performed to validate the accuracy in forecasting the energy demand for sustainable environmental planning and management.

Water services have been beneficial for many decades to both individuals and their economies. These programmes provide various services in which the drinking water and sanitation needs cannot be fulfilled in many parts of the world. Many of those waters will also help resilient biodiversity habitats and sustain them. Rising, inadequate and decayed facilities, inappropriate flux withdrawals, industrial and cultivation pollution, nutrient burden eutrophication, irrigation return flux salinity, exotic animal and plant infestation, improper harvesting of fish, flood land, and ecosystem changes in growth based on learner process.

Here, an adaptive intelligent approach is a subset of Artificial Intelligence Technology (AI) that effectively model environmental planning for sustainable water production. Modeling of artificial intelligence increases water quality by making knowledge slimmer and enhancing decision-making based on evidence-based on a mixture of computational AI methods and intelligence. Markov's Decision Process (MDP) in AIDWRP tackles complex water management with annual usage. It recognizes local weaknesses that establish sensitivity-driven approaches to optimize multiple policy areas to allow environmental management and effective ecological planning.

The rest of the paper is organized as follows: Section 1 and Section 2 discussed the introduction and related works on sustainable development of water environment based on ecological engineering intelligent planning. In Section 3, Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP) has been proposed. In Section 4, the numerical results have been analyzed, and the consistency of the data is evaluated. Finally, Section 5 concludes the research paper with a future perspective.

2. Related works

Ajay Gajanan Bhave et al. (Fritz et al., 2019) introduced the Decision-Making Under uncertainty (DMUU) approach for water resource planning. A water supply model is satisfactorily optimized and validated with the observed streamflow. In model simulations, almost all conditions increased the potential to meet such performance metrics without adaptation. The change options partly compensate for the effects of change, and the sequence of choices in adaptation processes according to stakeholder priorities impacts metric fulfillment. Early emphasis on agricultural demand control increases robustness and trade-offs between intra-basin water quality and basin-wide water availability. They prove that the best balance between demand and water supply is prone to future uncertainty and changes.

Qiang Wang et al. (Osorio-Cano et al., 2019) proposed the Pressure-State-Response and Matter-Element Extension (PSR-MEE) model for evaluating water resource sustainability. To assess the weight of the indexes, the coefficient of variance method was used. Sustainable water supplies are quantified based on data quality. The results indicate that water supply sustainability was relatively low and cannot ensure sufficient usage in the long term. The findings of the evaluation provide a guide for decision-makers in developing policies for water resources.

Manuela Carini et al. (Bierbaum et al., 2020) suggested the Least-Cost Optimization Model (LCOM) for water distribution networks with multiple supply sources and users. Sustainable use of water supplies at the national and municipal levels is of strategic significance. The sustainable use of water supplies leads to economic and social change and contributes to a proper sustainable environmental development process. This approach requires resolving the optimization problem based on a nonlinear function commensurate with the water distribution network cost. Pre-existing pipeline costs are known to be zero. Here, a realistic situation is considered, which would compensate for the maximum flow rate permissible for existing connections between sources and users.

David Haro-Monteagudo et al. (Modgil et al., 2020) initialized the Cascade Modeling Approach (CMA) for the long-term sustainability of an extensive water resource modeling under climate change. Hence, indices based on the duration, frequency, and magnitude of the supply shortage assessed the system performance and sustainability. The results demonstrate the current management scenarios, particularly for irrigated agriculture, for the system's future viability. These results show that current water resource strategies in this area should be reviewed based on climatic change.

Chakaphon Singto et al. (Endl et al., 2019) proposed the Bayesian Belief Networks (BBN) to explore water resource interventions' codesign options. The BBN framework effectively stimulated stakeholders to look at the positive and negative elements of different ways of intervening on water resources with a Bottom-up assessment of water resources' environmental planning.

In the modern age, water is a significant resource to preserve socioeconomic stability and sustainable ecosystems. Water services are adequately managed as a crucial part of the growth that decreases vulnerability and wealth. Conventional water system control is concerned with optimizing current flows to fulfill all conflicting needs, including water and sediment on site. Climate change will also exacerbate the unique problems in the control of water supplies by leading to instability.

Based on the survey, it is observed that sustainable development of water management in urban areas for environment management and planning is an essential characteristic of challenge. This research has overcome this research using the AIDWRP, the subset of AI with high reliability without compromising hydrological, environmental, and physical integrity. Sustainable water resources, policies, and integrated resource management are integral features under which all water problems and appropriate solutions can be brought together, and their socioeconomic and environmental concerns. The following defines the challenges and opportunities to design an efficient model for sustainable water resource management using AIDWRP and MDP in urban areas. The findings indicate that the artificial intelligence modeling system with proposed AIDWRP can be utilized to manage and decision-making in urban water resources management.

3. Adaptive intelligent dynamic water resource planning (AIDWRP)

In this paper, AIDWRP is the subset of AI proposed for sustainable dater management development in urban areas. The broader scope of use of artificial intelligence algorithms in water supplies is to increase the total performance of water infrastructure activities such as asset control and repairs, energy conservation, and carbon and water footprint reduction, thereby enhancing the quality and expense of the services provided. Artificial intelligence aims to develop water infrastructure to enforce climate protection strategies, water safety strategies, disaster risk management plans, sponge cities, and advanced water supply management. Sustainable water resource management (SWRM) includes distributing financial and social services necessary for supporting water systems for sustainable environmental planning and management. Urban water management aims to build resilience, living, productive, and sustainable cities and towns. SWRM evaluation requires accountability of the overheads' actual costs to manage water sectors. The socioeconomic and environmental aspects that often do not easily translate into the quantitative values necessary to plan, decide, monitor, and evaluate them rigorously. Assessment models include future indicators for environment sustainability to compare management practices across several agencies and environments to site modeling analyzes that enable individual managers and governments to evaluate progress towards sustainable practices. This paper aims to build a statistical model for seasonal water demands. Locational release constraints and annual consumption constraints for sustainable water resource management in urban regions are analyzed and represented in Fig. 2.

4. Problem statement

Let's consider a basin with J hydropower plants in an urban area, and every hydropower plant has its water tank. The water depletion, irrigation, and water consumption of all water tanks must be determined over a specified horizon (R), conditional on operating constraints of hydraulic coupling, and individual water tank. The objective is to increase the overall hydraulic return. The AI-assisted decision-making period occurs for 1 or 2 weeks, usually one year for the planning horizon. It is assumed that discussions will be simplified without losing generality.

(i) The delay in water flow between storages is analyzed using the AI-assisted decision-making for long-term preparation.
(ii) The network of the tank is acyclic as assumed.
(iii) The water is discharged directly from a tank that enters one reservoir alone.

The model actions, states, and dynamic are formulated as follows: For all $r = 0, 1, \ldots R-1$, the state $Y(\mathrm{r})$ at step r includes the loading $y_j(t)$ and the collected water consumption $n_j^c(t)$ in period c of water tank j, $j = 1, \ldots J$. Remember that the leakage has no return and does not produce energy, and the consumed water is utilized for urban supplies, industrial, farming irrigation.

Fig. 2. Functions of Urban Water Management.

Let's consider the control action $B(t)$, and model state $Y(t)$, the system dynamic at step r is identified as follows: $\forall r = 0, 1, \dots R-1, j = 1, \dots J$. Furthermore, Eqs. (1) & (2) discussed the dynamic water resource management issue with annual use in the AIDWRP method.

$$y_j(r+1) = y_j(r) - v_j(r) - r_j(r) + \sum_{i \in V_j} [t_i(r) + \lambda_i v_i(r)] + \xi_j(r) \tag{1}$$

$$n_j^c(r+1) = \begin{cases} n_j^c(r) + v_j(r), if\, r_c \le r < r_{c+1} \\ n_j^c(r), otherwise \end{cases} \forall c = 0, 1, \dots C-1 \tag{2}$$

Eq. (1) represents the water equilibrium of the cascaded water tanks, where $y_j(t)$ is the water tank storage j at period r and first stage storage $y_j(0)$ is assumed as $t_j(r)$ The water discharge stated as Eq. (2) is used to improve the dynamic water resource management issue with annual use in the AIDWRP method.

$$t_j(r) = s_J(r) + w_j(r) \tag{3}$$

Eq. (2) indicates the accumulated consumption of every period and lets set the first stage $n_j^c(0) = 0$ for $c = 0, 1, \dots C-1$. V_j is the set of straight upstream water tank j. The inflows to the water tank j include the natural inflows, water recession, and water release from the consumption of an upstream water tank. $\xi_j(r)$ Is the natural influx of water tank j at time r, a random parameter with a specified dispersal. λ_i The recession ratio of water tank i, which denotes the ratio of consumption returning to the water model. Fig. 3 demonstrates the dynamic planning and control of problem farming.

This is partly due to the local existence of models designed for unique farming environments and the sophistication of the underlying mathematical models. This paper seeks to establish a complex programming model for maximizing long-term water resource planning and control problems. The probability of covering various restrictions is addressed via state-space production, and the production process for water rotation rules is seen. The target function represents the farmers' benefit maximization goal and is specified concerning the harvest's randomness.

Definition 1. The water recession is a percentage of water consumption returning and turns into a portion of influxes to the downstream water tank that is revised, as exposed in Eq. (1).

The practicable action set at step r with condition $Y(t)$ is expressed as follows,

$$\underline{y}_j \le y_j(r) \le \overline{y}_j$$

$$0 \le s_j(r) \le \overline{s}_j$$

$$w_j(r) \ge 0,$$

$$\sum_{i \in V_j} t_i(r) \ge \varphi_j \tag{4}$$

As inferred from Eq. (4), it denotes the physical bounds for storage, discharge, spillage, and consumption for $j = 1, 2, \dots J$ where φ_j is a lower limit of controlled influxes to water tank j each stage, and it needs less flow to every hydro plant to avoid water cut-out.

Definition 2. To avoid water cut-outs, the locational release constraints are measured, as shown in Eq. (4) for sustainable environmental management and planning.

The objective function and reward structure are measured, in which one stage reward function at step r is the hydro production benefit for $r = 0, \dots R-1$.

$$f_r(Y_r, B_r) = b_r Q_r^2 + a_r Q_r + d_r \tag{5}$$

As discussed in Eq. (5) where the quadratic polynomial is denoted as benefit function concerning the overall hydro production q_r in a stage r. Eq. (5) The hydro production utility is used to improve the nonlinear rewards in Markov Decision Process (MDP),

$$q(r) = \sum_{j=1}^{J} \sigma_j s_j(r) \tag{6}$$

As derived in Eq. (6) where $s_j(r)$ is the water release from the water tank j in step r.The terminal reward at step R reflects the penalty price for the seasonal demands violation for water irrigation and annual consumption and urban resource constraint,

$$f_R(Y(R)) = -N \cdot \sum_{j=1}^{J} \sum_{c=0}^{C-1} 1\left(n_j^c(R) < v_j^c\right) = -M \cdot 1\left(\sum_{j=1}^{J} \sum_{c=0}^{C-1} n_j^c(R) > \overline{v}\right) \tag{7}$$

As inferred from the Eq. (7) where N is an adequate high number denoting the penalties, 1(.) is a pointer function which is equivalent to one if logical expression (.) is accurate, $n_j^c(R)$ represents the overall water consumption of water tank j within season c in line with Eq. (2) that is,

$$n_j^c(R) = \sum_{r=r_c}^{r_{c+1}-1} v_j(r) \tag{8}$$

As shown in Eq. (9) where $j = 1, 2, \dots J$, $c = 0, 1, \dots C-1$. Eq. (7) denotes the penalty for seasonal demands violation for urban supply and water irrigation, where v_j^c is a constant for indicating the water consumption seasonal demand at water tank j in demand time c. The second term in eq. (7) shows the penalty for the yearly consumption violation restraint, where $\overline{v}$ is a provided upper limit of yearly water consumption in the urban area inside the horizon R. The assessment of v_j^c and $\overline{v}$ are provided based on government regulation,

$$\sum_{j=1}^{J} \sum_{c=0}^{C-1} v_j^c \le \overline{v} \tag{9}$$

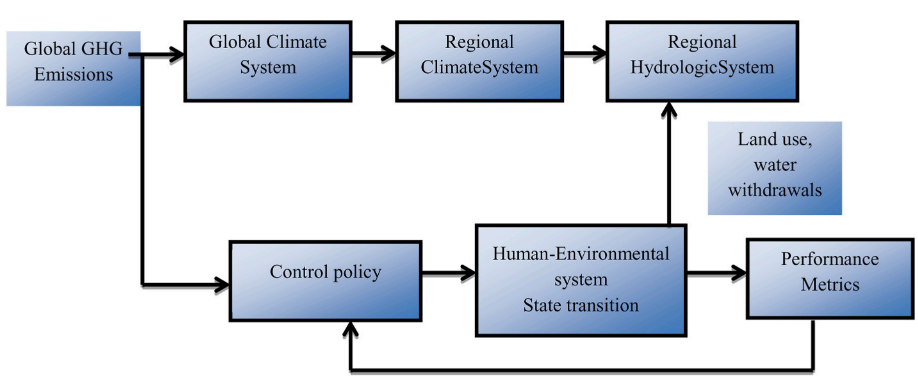

Fig. 3. Dynamic Planning and Control Problem Farming.

Definition 3. This study measures the seasonal water demands in every water tank for urban supply and irrigation; water consumption is ensured. Remember that the penalty considers this constraint in Eq. (7).

The suggested AIDWRP approach in the urban water context shown in Fig. 4. The water supply in the region comprises the essential urban economic substructures as social and natural characteristics. Water occurs in urban environments because of its sustainable, atmospheric, financial roles of space-time delivery. The artificially improved biological water management network is the city water environment. This comprises a natural and social water environment in which a sustainable water environment is used for the natural water conditions for an active economic water environment. The urban natural water system focuses on recharging by the precipitancy, evaporation, perspiration, surface fluke, and soil absorption, among the surface water, atmosphere, and groundwater. The natural water cycle has a substantial impact on the urban climate, which involves reestablishing water resources. Rainfall is one of the most significant aspects of the city's natural water network and has a vital role in reestablishing water supplies in the environment. Precipitation reaches the rivers network and ground waters, significantly affecting their slope, permeability, the texture of the soil, and the intensity of rainfall.

Definition 4. This study reflects the annual consumption constraint by planning the upper bound consumption of water in which urban areas help balance the utilization of limited water resources within various urban regions. Note that the penalty considers this constraint in Eq. (7).

The objective function aims to increase the predictable overall reward in excess of finite-horizon R,

$$\max_{\pi} : \eta(Y_0, \pi) = G\left\{ \sum_{t=0}^{T-1} f_t(Y(r), B(r)) + f_R(Y(R)) \right\} \tag{10}$$

As inferred in Eq. (10) where the first stage Y_0 is given, policy planning π that contains a sequence of decision guidelines which are associated with action space and state space, Eq. (10) helps to improve the stochastic dynamics in Markov Decision Process (MDP),

$$\pi = (\pi_0, \ldots \pi_{T-1}) \tag{11}$$

$$B(t) = \pi_t(Y(r)), \forall t = 0, \ldots R-1 \tag{12}$$

Through the Markov Decision Process, the water resource planning with annual consumption and locational release has been formulated in this study using Eq. (12). It helps to improve the locational constraints and develops sensitivity-driven methods to optimizing policies.

Fig. 5 shows the artificial intelligence-based urban water resource management and planning. Accurate water demand forecasts have been utilized based on artificial intelligence modeling for capacity planning, scheduling management, financial planning, tariff adjustment, and optimization of a water delivery organization's operations across short, medium, and long term horizons. In the field of efficient water supply, artificial intelligence or machine learning is specifically used for decision-making: how water sources should optimize the information available to help determine while maximizing the delivery of services and how to reduce running costs, including social and environmental

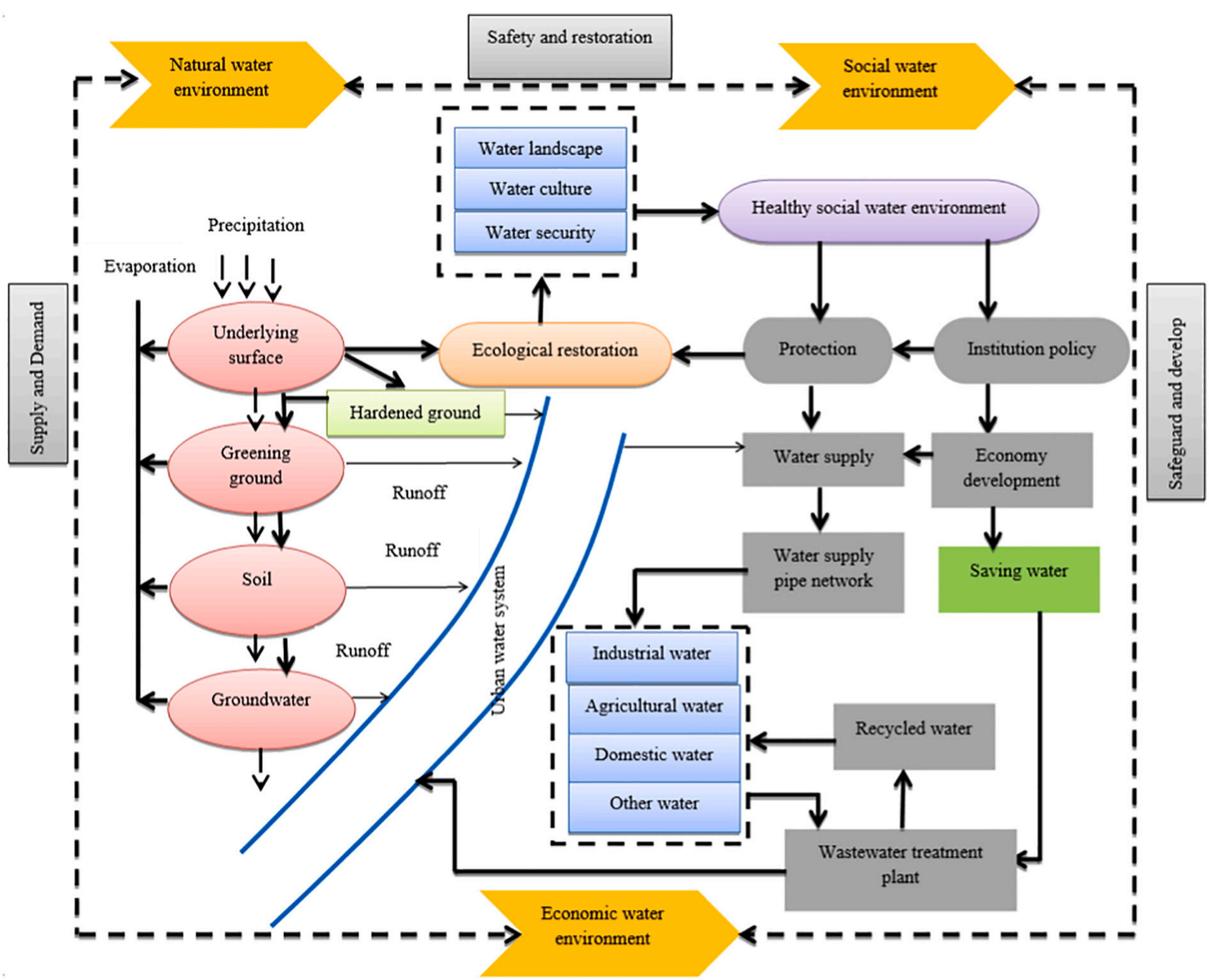

Fig. 4. The proposed AIDWRP method in an urban water environment.

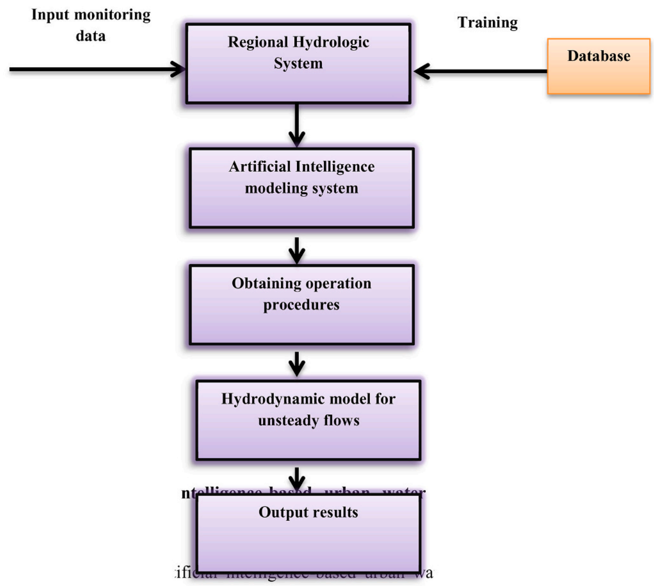

Fig. 5. Artificial Intelligence-based urban water resource management and planning.

externalities. Water utilities follow the example of other sectors, particularly energy, at times with fully understanding the underlying hypotheses and implications for applying information and communication technology. Therefore, the artificial intelligence modeling system can be reflected as a tool for efficient urban water resources management.

Definition 5. Sensitivity based methods are initialized to optimize the Markov Decision Process with action spaces and discrete state. Let's deliberate a discrete-time Markov chain,

$$Y := \{Y(0), Y(1), \dots Y(R-1), Y(R)\} \tag{13}$$

As shown in Eq. (13) where continuous state space $Y \in \mathbb{R}^m$ and R is the finite horizon. Let A be the σ filed of comprising all the Lebesgue measurable sets. The state $Y(r) = y \in \mathbb{R}^m$ at time r, $r = 0, 1, \dots R-1$, the likelihood that the subsequent state relies on a set $a \in A$ at period $r+1$ can be indicated as a transition state expression $Q_r(A|y)$ which meets,

$$Q_r(\mathbb{R}^m|y) = \int Q_r(dx|y) = 1, \forall y \in \mathbb{R}^m \tag{14}$$

Let's define linear right operator Q_r respective to $Q_r(A|y)$ on the function space, To released locational constraints and develops sensitivity-driven methods to optimizing policies in Markov Decision Process (MDP),

$$Q_r e(y) := \int e(x) Q_r(dx|y) \tag{15}$$

As discussed in Eq. (15), where $e(x)$ is a quantifiable function. The invention of two operators Q_r and Q_r' is stated as $\forall y \in Y$, $a \in A$, there is a specific relief from the engagement of supply and demand for water resources and substantial improvements in local economic efficiency.

$$\left(Q_r, Q_r'\right)(A|y) = \int Q_r'(A|x) Q_r(dx|y) \tag{16}$$

A likelihood measure $u(A)$ can be observed as a particular state transition expression $u(A|y)$ which receipts the similar importance $u(A)$ for everyy $\in \mathbb{R}^m$. Therefore, the likelihood extent $u(A)$ can be observed as an operator u. The state dispersal at period r is indicated as α_r. With the provided first state distribution α_0, it can be determined as,

$$\alpha_r = \alpha_{r-1} Q_{r-1}, \forall r = 1, 2, \dots R \tag{17}$$

Let $f_r(y)$ be a cost function at time r concerning state y. The Markov chain's overall cost in excess of finite-horizon R is shown in Eq. (18) to improve the water resources and substantial improvements in local economic efficiency.

$$\eta(y) = G\left\{ \sum_{r=0}^{R} f_r(Y(r)) | Y(0) = y \right\} \tag{18}$$

Definition 6. Potentials and performance sensitivity expression for state y at timer is determined by Precipitation, which reaches the rivers network and ground waters that are significantly affecting their slope, permeability, the texture of the soil, and the intensity of rainfall.

$$h_R(y) = f_R(y),$$

$$h_r(y) = f_r(y) + Q_r h_{r+1}(y), \forall r = 0, \dots R-1 \tag{19}$$

Let's consider (Q_r, f_r) and (Q_r', f_r') be the performance and transition functions at periodr of dual Markov chains with the similar state-space $Y \in \mathbb{R}^m$ where η, h_r, α_r and η', h_r', α_r' be their resultant potential functions, overall performances, and the state distribution at periodr, correspondingly. Furthermore, to improve the nonlinear rewards, stochastic dynamics and hydraulic constraints are upgraded above the equations in Markov Decision Process (MDP).

In AIDWRP, Markov Decision Process (MDP) discusses the dynamic water resource management issue with annual use and released locational constraints that develop sensitivity-driven methods to optimize several efficient environmental planning and management policies. Consequently, there is a specific relief from the engagement of supply and demand for water resources, and substantial improvements in local economic efficiency have been simulated with numerical outcomes.

5. Experimental results and discussion

(i) Utilization of water resources

Urban water systems have revolutionized into large, highly engineered systems in which extensive pipeline networks import water from surrounding catchments and aquifers. In large irrigation systems, the used water would primarily be collected and processed to remove the pollutants and nutrients restored to rivers and the sea. These systems provide the population and industry with reliable, clean water and protect the public; however, there is concern that water services may be much more efficient than merely importing water, disposing of wastewater, and collecting stormwater. People must use local water sources more efficiently, with populations expanding, water resources being highly decentralized, and climate change reducing water supplies from catchments and aquifers. The artificial intelligence modeling system has been applied to a flood risk control process. Fig. 6 shows the utilization of water resources in urban areas using the proposed AIDWRP method. Here computational tools are used for analysis.

(ii) Irrigation water supply reliability

The artificial intelligence-based water system is influenced both externally and internally, representing the ability to supply water. Impacts are caused by failure and depletion of water by the water supply system components. During water system operation, the change in their planned function project (water distribution) affects various kinds of energy (mechanical and thermal). Every water supply system's goal should be to reduce water losses and increase reliability, as this will improve the economic and environmental performance and will certainly provide users with more exceptional service. Every water supply system should reduce water losses and increase reliability

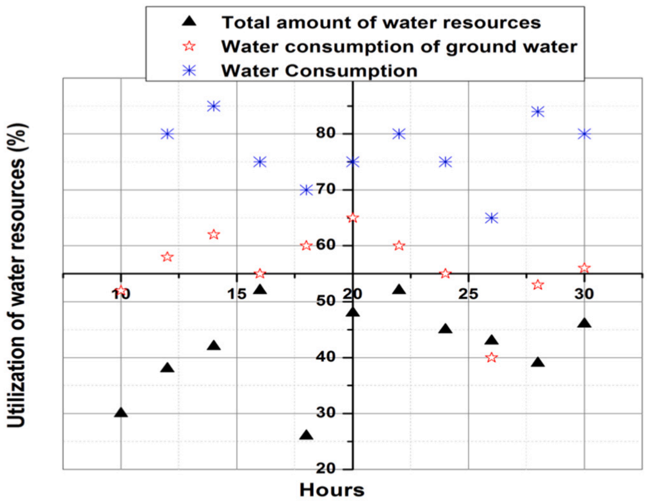

Fig. 6. Utilization of water resource

because this leads to better economic and ecological performance, certainly better service for users. Dependability may be considered the water supply system's ability to operate when one or more components fail. Similarly, despite the failure and complex operating conditions, the system can be seen to provide a service on an acceptable level. It is impossible to create reliable water supply systems by fundamental indicators, which are essential for indicating technical conditions, without reliability standardization. A list of signs and their labeling necessary has been determined for the water supply system's quality under the term reliability standardization. Fig. 7 demonstrates the irrigation water supply and demand employing the proposed AIDWRP method.20.

(iii) Overall Performance Ratio

A sensitivity-based optimization method is established to resolve the finite-horizon MDP with its constant states and action spaces. A statistical derivative model based on artificial intelligence has been developed to address the finite horizon's decision-making issue is a continuous Markov decision process. The latest method's most important feature is the constant improvement of its performance, and the complex combination between computational accuracy and efficiency cannot be established. The model suggested in the study is shown to capture the annual water use and release regulations effectively when compared to other existing approaches. Fig. 8 displays the overall performance ratio adapting the suggested AIDWRP system.

(iv) Accuracy Ratio analysis

The true costs of establishing and supplying water sources will be expressed in water levels and allocations. According to an integrated urban water management strategy based on artificial intelligence, accurate prices will encourage water management for sustainable environmental management. The reorientation and use of various management strategies and wise combinations depend on the local situation required for urban water policy in more efficient directions. The interaction with the urban water cycle in such a way: ensures water protection by efficiently utilizing the various available water sources. Demanding strategies include the adoption of water-efficient appliances such as washing machines, washing machines, and bowls. The use of drought-tolerant species efficiently vegetated along the irrigation systems and garden watering education increased performance. For specific applications, water from rainwater, stormwater, or recycling can be used for drinking water. The water supply system may often be improved by less demand to provide the same service, which reduces the distribution losses through the control of leakage and pressure management. The proposed AIDWRP method enhances the accuracy ratio in forecasting water demand and supply in urban areas. Fig. 9 demonstrates the accuracy ratio analysis utilizing the suggested AIDWRP model.

(v) Efficiency Ratio

The proposed AIDWRP based on artificial intelligence includes evaluations to determine water supply quantity to evaluate present and future needs for the expected climatic change impact. This acknowledges the significance of water usage sustainability and economic performance in which water operations become challenging to manage. It recognizes that various kinds of water can be utilized for diverse purposes. For example, inhabiting water (surface water, rainwater, and groundwater) or wastewater (brown, black, yellow, and gray water) can be appropriately preserved to fulfill agricultural, industrial, and environmental demands. It identifies that residing water can be used for various types of use. Saltwater has become an available water supply with efficient new desalination technologies. Efficient use of water delays complicated and expensive production increases, such as new dams and desalination plants. It is always less costly to people per unit consumption than to obtain, store, and deliver additional energy. Management of demand will increase wastewater flows per unit, creating additional capacity for population growth in current wastewater

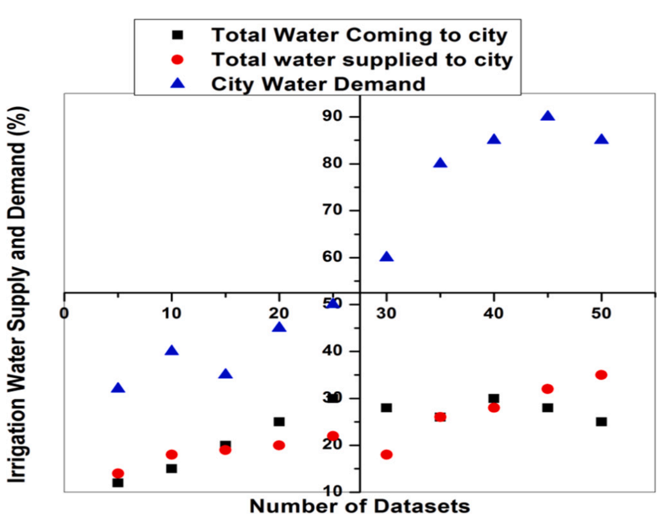

Fig. 7. Irrigation water supply and demand

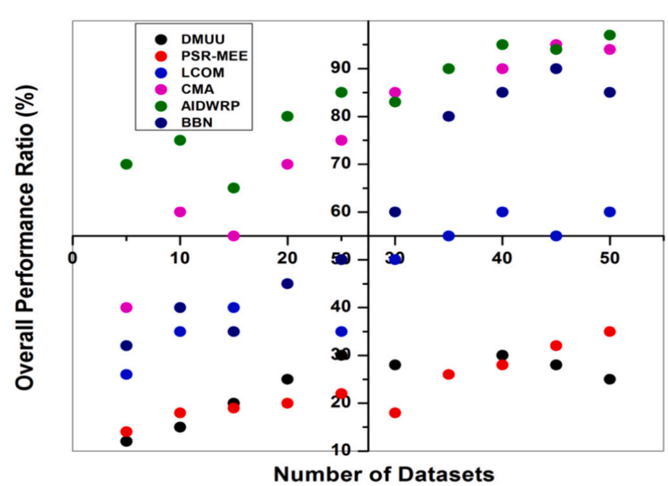

Fig. 8. Overall performance Ratio

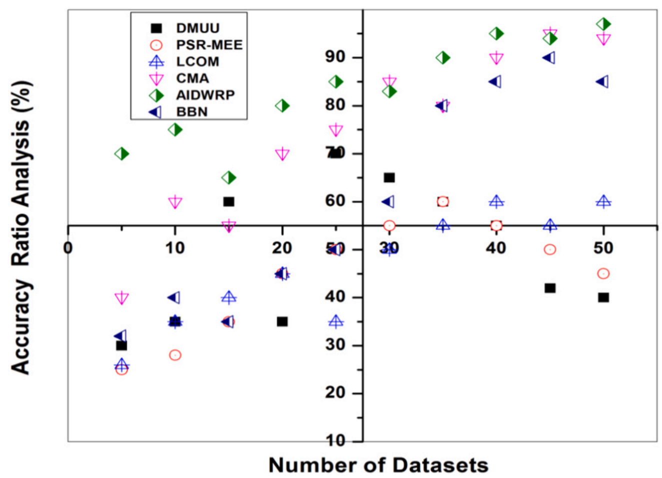

Fig. 9. Accuracy Ratio analysis

treatments. Fig. 10 displays the efficiency ratio using the suggested AIDWRP system.

The proposed Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP) based on artificial intelligence for sustainable development of water management in urban areas achieves high performance and accuracy in determining the water consumption, supply and demand when compared to other existing Decision-Making Under Uncertainty (DMUU) approach, Pressure-State-Response and Matter-Element Extension (PSR-MEE) model, Least-Cost Optimization Model (LCOM), Cascade Modeling Approach (CMA), Bayesian Belief Networks (BBN) methods. Consequently, there is a specific relief from the engagement of supply and demand for water resources, and substantial improvements in local economic efficiency have been simulated with numerical outcomes.

6. Conclusion and research perspectives

This paper presents AIDWRP to sustain water management in urban areas. If the environment is recognized as a legitimate water user, and its more excellent distribution is allocated, ecological, environmental, and hydrological integrity must be achieved. The adverse effects on water resources development will be mitigated. It will ensure sustainable water resources development if future climate scenarios have been incorporated in water resource planning and development. To ensure the protection, preservation, and improvement of existing environmental conditions, an environmental assessment should be conducted that satisfies the agreed standards. Markov's decision-making process approach for the management and planning water resources on a given finite horizon is presented. An agent must define a subset of transfer points and use an MDP to model the subnetwork's dynamic and uncertainties surrounding those transfer points. The optimization problem is defined as the reduction of water supply costs subjected to a constraint to water requirement. The groundwater drawdown can proceed without regulation until pumping cost exceeds the user's value of curtailment. The proposed AIDWRP method enhances the performance and accuracy ratio when compared to other existing methods. The findings indicate that the artificial intelligence modeling system with proposed AIDWRP can be utilized to manage and decision-making in urban water resources management. Markov's Decision Process (MDP) in AIDWRP tackles complex water management with annual usage. It recognizes local weaknesses that establish sensitivity-driven approaches to optimize multiple policy areas to allow environmental management and effective ecological planning. Accordingly, the dedication to water management supply and demand has been alleviated, and significant increases in local economic performance have been simulated with observed effects.

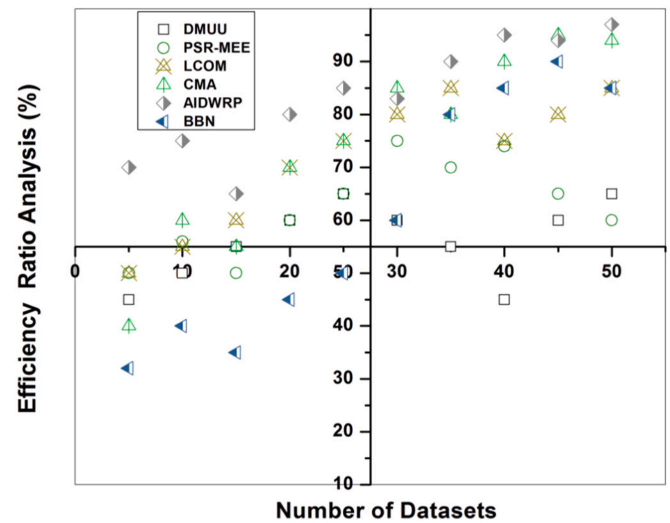

Fig. 10. Efficiency Ratio.

Declaration of Competing Interest

None.

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