Are the Days of Field-to-Laboratory Analysis Gone? Effects of Ubiquitous Environmental River Water Quality Assessment

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Abstract. As the human population growth and industry pressure in most developing countries continue to increase, effective water quality assessment has become critical for river waters. A major challenge, however, faced in water quality assessment is the process of data capturing and chemical laboratory approaches, which could be expensive and time consuming. This work develops ubiquitous particle swarm optimization (PSO) made-easy framework for mobile networks. The framework experimentally assesses water health status of Southern Africa river waters. Simulation results show that the proposed framework is able to obtain good results with economical solution when compared with assessment results obtained by the state of the art.

Keywords: Framework · E-Services · Environment · Ubiquitous network · PSO · Water quality · Fuzzy · Developing country

1 Introduction

The rate of increase in population, urban, and industrial activities has raised researchers concern about water quality. Surface water quality in a suburban depends on the nature and extent of industrial, agricultural, and other activities in the catchment. Therefore, surface water contamination from agricultural and urban runoff and waste water discharges from industrial activities is of major concern [1]. Water quality is determined by assessing biological, chemical, and physical characteristics. Due to their dynamic nature and easy accessibility through tributaries, rivers are affected by contaminants.

Pathogenic microbes spread directly through contaminated water cause waterborne diseases. Most waterborne diseases cause diarrheal illness. Eighty-eight percent of diarrhea cases worldwide are associated to unsafe water, inadequate sanitation, or insufficient hygiene. These cases result in 1.5 million deaths yearly affecting mostly young children in developing countries [2]. Figure 1 shows total water-related deaths in the years 2000–2020 years. Red lines show ranges of death likely to occur without United Nations Millennium Development Goals (UN MDG). Blue lines show range of deaths even if MDGs are achieved.

Recently, surface water quality monitoring and evaluation has attracted attention of scholars. To protect water quality resources, scholars work on pollution degree and the

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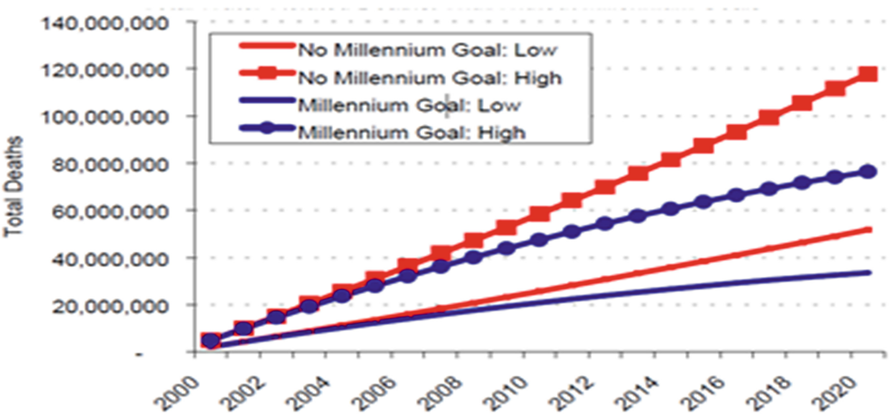

Fig. 1. Total Water-Related Deaths between 2000-2020 [5]. (Color figure online)

development of trends models in surface waters. Various techniques for monitoring and predicting surface water quality were developed [3]. In [4], a multi-variate, principal component analysis (PCA) was applied to evaluate correlation of river water parameters. This work demonstrates that PCA results for physico-chemical parameters are less important in explaining the annual variance of the data set. However, only one-year annual mean values of water quality parameters were used in this study.

Finally, in [6] a comparison of biotic and physicochemical indices approach is presented for monitoring and assessing water heath quality of a river. The approach used biotic and 28 physico-chemical and habitat parameters to calculate six indices to assess water quality and the impact of human activities in the Tajan River, Iran. Results showed a reduction in water quality and ecological from upstream to downstream. The reduced water quality was revealed by biotic indices better than the abiotic indices that were linked to a variety of ecological water scales.

There exist several optimization techniques for assessing the quality of water. However, particle swarm optimization (PSO) presents many advantages over other swarm intelligence techniques. Yet in spite of its simplicity and few parameters involved, PSO still presents a number of drawbacks, such as being stuck in local minima. It is therefore of special relevance to address these drawbacks for the benefit of other researchers.

1.1 Contributions and Outline

Rapid evolution of ubiquitous technologies in developing countries is spreading rapidly and has motivated an explosion of initiatives to explore the use of these technologies in a number of water issues. Smart phones are becoming pervasive computing, communications platform, and the variety and number of mobile applications has increased recently. Since mobile phones are affordable, easy to use and can transmit multiple types of information over long distances, the development of ubiquitous network utilizing these devices is of great significance for e-Services. Ubiquitous devices can collect and transfer data in a variety of formats: voice, text, images and video and augmented reality.

This research study therefore focused on utilizing ubiquitous devices in resources management. Therefore the major contributions are:

- Development of a PSO made-easy model for ubiquitous framework, which minimizes time lag and risks in field-to-laboratory water quality assessments.
- Modelling the theory of Newton's laws of motion equations into PSO made-easy model integrated onto ubiquitous devices for assessing water health status of rivers in developing countries, such as Mohokare River.

The structure of this paper is as follows: In Sect. 2, we briefly review variants of PSO models and laxities of modeling water quality assessment. Section 3 proposes the ubiquitous network integration with PSO made-easy model in water quality assessment. Experimental evaluations on Mohokare River water health status is presented in Sects. 4 and 5 outlines the conclusions.

2 Theoretical Background

2.1 Variants of PSO Models

In this section, we review the available basic variants of PSO models, together with their advantages and disadvantages. The existing basic PSO variants are velocity clamping, inertia weight, constriction coefficient, synchronous versus asynchronous updates.

Basic PSO Model. A more detailed description of PSO algorithm is presented in [7, 8]. In PSO, the potential solutions, called particles, move iteratively within the search area according to the historical experiences of their own and that of their neighbors. The position of particle $\boldsymbol{i}$ at iteration $\boldsymbol{t}$ can be expressed as

$$x_i^t = \left\{x_1^t, x_2^t, \ldots, x_n^t\right\},$$

and the velocity of the i^{th} particle at iteration t can be expressed as

$$v = \left\{v_1^t, v_2^t, \ldots, v_n^t\right\}.$$

In order to reach the solution, each particle changes its searching direction according to these factors: the particle's best position, called p_{best} and the best particle's position in the entire swarm called g_{best}. In [9] the p_{best} and g_{best} are called cognitive and social parts respectively. During PSO iteration, the particle's velocity is updated according to its local information and particle's global position using Eq. (1). The particle's position is updated using Eq. (2).

$$v_i^{t+1} = v_i^t + c_1 \times r_1\left(p_{best} - x_i^t\right) + c_2 \times r_2\left(g_{best} - x_i^t\right). \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

In [10], analysis of PSO is carefully looked at. Since PSO is based on intelligence, it can be applied into both scientific research and engineering. PSO does not have overlapping and mutation calculation. Search can be carried out by the speed of the particle. Only the most optimistic particle can transmit information onto other particles, and the speed of researching is fast. Another advantage of PSO is that it adopts real number codes, and is decided by the solution. Consequently, PSO has its drawbacks as it easily suffers from partial optimisms, which causes less exact at the regulation of its speed and the direction. The PSO method cannot work out problems of scattering and optimization and problems of non-coordinate system.

Modified PSO Exploiting Areas around Known Solutions [11]. The drawbacks of PSO have let to developments of several PSO variants. These variants improve the speed of convergence and quality of solution found by PSO. Quite a number of control parameters influence these PSO variants. In this section, we discuss the modified PSO variants that exploit areas around known solutions.

Synchronous versus asynchronous updates. In synchronous update, particles update their velocities considering the current best position found by their neighborhoods. The fitness of all particles is computed and shared within neighbors. This leads to a slower feedback and better g_{best}. On the other hand, in asynchronous update, particles update their velocity immediately after computing the fitness function and consequently, the update is performed with particles having imperfect information about their neighborhoods.

Velocity clamping. Velocity clamping controls the global exploration of the particle. Suppose velocity v of a particle i exceeds the maximum allowed speed limit, velocity clamping assigns that particle the maximum velocity allowed. Velocity clamping reduces the size of the step velocity and controls the movement of the particle. However, should the velocities equal to the maximum velocity; particles will continue searching within a hypercube and would likely remain in the optima without convergence. Velocity clamping is adjusted using Eq. 2 in [12].

Constriction coefficient. Constriction coefficient is used as a natural, dynamic way to ensure that particles converge to a stable point without clamping. The velocity update Eq. (1) becomes (7) in [12].The constriction coefficient approach is employed under the constraints that $\beta \geq 4$ and $k \in [0, 1]$, and this constraints guarantees that the swarm converges.

Modified PSO with Inertia Weight Exploring New Areas of the Search Space

Inertia weight. In the original PSO, inertia weight controls particle's exploration and exploitation. It controls the momentum of the particle by weighing the contribution of the previous velocity. Inertia weight also eliminates the idea of velocity clamping. An inertia weight w is introduced into the Eq. (1) and the original equation becomes Eq. (5) in [12]. Inertia weight has been developed by some researchers [11].

Dynamic Environment with PSO. In dynamic environments, the PSO should be fast to allow quick re-optimization. The idea is to find a good solution before the next environment can change. A dynamic environment changes the standard velocity update equation to (9) as in [12]. Several solutions were developed for dynamic environments.

Multi-objective optimization with PSO. The multi-objectives optimization (MOO) problem is defined as:

$$\begin{aligned} \text{minimize}: & \ f(x),\ x = (x_1, x_2, \ldots, x_n) \\ \text{subject to}: & \ g_i \leq 0,\ i = 1, \ldots, m \\ & \ h_i = 0,\ i = 1, \ldots, p \end{aligned}$$

The objective of the MOO approach is to find a set of solutions that will optimally balance the trade-offs among the objective of a MOP. This approach differs from the basic PSO that return one solution [11].

Niching with PSO. Niching algorithms are algorithms that locate multiple solutions. Speciation is the process of finding a niche [11].

Single solution PSO. Single solution PSO development is to obtain single solutions to continuous-valued, unconstrained, static, and single-objective optimization problems [13].

2.2 Survey on Laxities of Water Quality Assessment Models

River water quality has become a hot research topic for many scholars. Researchers are engaged in finding quick and modern techniques for river water assessment. In [4], a multivariate analysis is used to assess the quality of water in a river. The first step is to collect data on a monthly basis during June 2005 to May 2006 collecting eight physico-chemical parameters from Bennithora River. Water samples were taken to the laboratory for further analysis. Principal component analysis (PCA) was performed to identify the potential reduction of physico-chemical parameters. Results showed that there was a potential for improving the efficiency and economy of the monitoring network by reducing the number of monitoring parameters from 8 to 3.

Chemometrics was used to assess the quality of water in Langat River [3]. Discriminant analysis (DA) was used to confirm the hierarchical agglomerative cluster analysis (HACA) results. The application of these different pattern techniques reduce the complexity of large data sets and proved to give better interpretation and understanding of water quality data. The projects mentioned above contributed significantly to river water quality monitoring. These projects demonstrate potential benefits achieved by laboratory and statistical techniques in environmental management. However, there are challenges faced by these approaches, including:

- Fieldwork for data collection takes a long time.
- There is a need for sophisticated laboratory buildings and laboratory instruments for data analysis.
- Collected water samples require specialized storing facilities.

- Collected water samples need to be transported from the field to laboratory hence specialized care should be maintained in terms of storage and handling not to distort data.
- Field workers need a special training in handling and taking specimen of parameters.
- It is expensive and manually intensive.

3 Proposed Ubiquitous Network Integrated with PSO Made-Easy Model

3.1 Establishing the Framework

In view of the above challenges faced with traditional techniques in water quality assessment, we describe in details our proposed design of ubiquitous network integration with PSO made-easy model for river water assessment. As illustrated in Fig. 2, the proposed framework consists of two layers: hardware and software layers. Hardware architecture is composed of field equipment for data collection (smartphones, personal digital assistant (PDAs, tablet computers)), a server computer with intranet and internet connection, workstations connected to the server allowing access and renewing data at the server. The framework shows mobile devices equipped with water sensors to detect water quality parameters, pH, Temp, Turb, TDS, and DO and these sensors provide general characteristics of water quality. Ubiquitous devices acquire data from sensors using a Bluetooth or Wi-Fi connection and then transmit data to the application server through broadband cellular connections. The transmitted data is in a

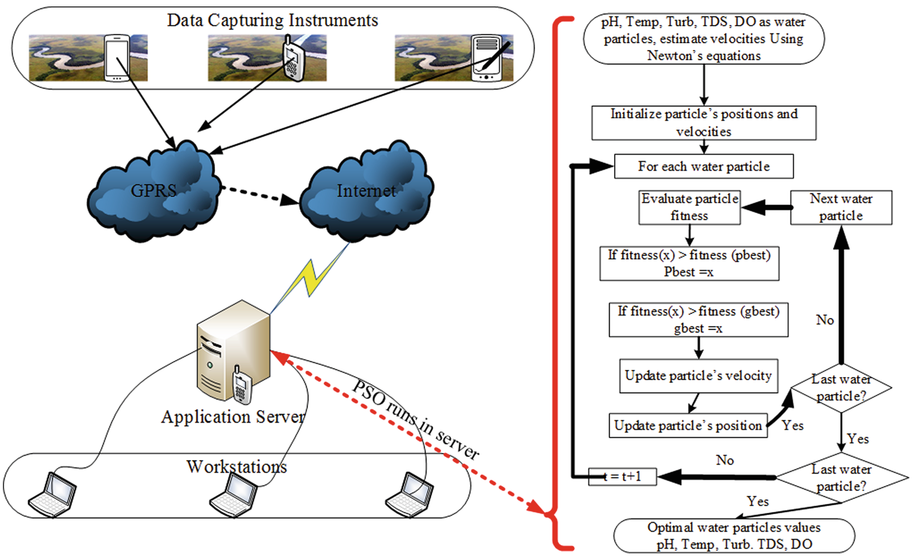

Fig. 2. Framework for ubiquitous network for pso made-easy model for river health status.

form of an SMS, which contains water parameter values. The software architecture is composed of PSO made-easy analysis and visualization tools. Raw data acquisition and transmission is performed at each mobile device using a custom-built integration software. A stream of data is transmitted to an application server running an intelligent PSO made-easy application. The framework allows users to reduce human power for data collection. It is much cheaper in cost and time. The devices consumes less power since and they are not connected with wires and these mobile devices are battery driven and it is easy to replace battery or recharge batteries. Data may be captured on hourly basis or at different times of a day and this helps in conserving the devices battery power. It is in the application server where actual water quality analysis is performed.

When developing the framework, issues taken into account were that:

- Data capturing equipment should better fit practical utility needs and should be easy to operate and maintain.
- Available technology should link to water quality regulations.
- Technologies and practices are developed to manage the large quantities of data transmission.

Additional benefits of the proposed framework are:

- It saves money.
- It speeds up data collection as data is transmitted thorough the network.
- It reduces time-consuming filed work.
- Storage of samples not needed which might require special storing facilities.
- It does not require laboratory analysis experiments.
- It does not need transportation.
- It does not need laboratory buildings.

3.2 Parameters of River Water Particles [14]

Water quality index (WQI) attempts an imperfect answer to non-technical questions about water quality. WQI is a unit less number ranging from 1 to 100 where a higher number indicates a better water quality. Multiple constituents are combined and results are aggregated to produce a single score for each sampling site. Water quality parameters used in defining WQI in this study are described as follows:

pH. pH measures the degree of acidity or alkalinity of the water. A pH of 7 is neutral, values below 7 are acidic, and values above 7 are alkaline. Some organism survives better in waters with pH between 6.5 and 8.5. Acceptable pH for drinking water ranges between 6.5 and 8.5.

Temperature. River water temperature is very important as it directly affects the biochemical process. Most aquatic life survives in certain temperatures. Temperature influences the acceptability of a number of other inorganic constituents and chemical contaminants that may affect taste. High water temperature enhances the growth of the microorganisms and increases taste, odor, color, and corrosion problems. The recommended temperature for drinking water shall not exceed 5°C.

Turbidity. Turbidity measures the transparency/clarity of water. The high measures of turbidity in water reduce light penetration resulting in waters being unable to support a wide variety of aquatic life. High turbidity can protect microorganisms from the effects of disinfection, stimulate growth of bacteria and give rise to a significant chlorine demand. The recommended turbidity level for drinking water is between 0.5 NTU to 1.0 NTU.

Total dissolved Solids. Total dissolved solids (TDS) measure the amount of solids materials dissolved in water. These materials include salts, some organic materials. If TDS is too high or too low, it might affect the aquatic life leading to death. Recommended TDS for drinking water is from 25 to 100 mg/l.

Dissolved Oxygen. Dissolved oxygen (DO), an important indicator of the water quality measures the amount of life-sustaining oxygen in the water. Lower levels of dissolved oxygen in water signify that there is a possibility of pollution. High levels of DO are good for drinking water as the water tastes better. Drinking standard for DO is 1.3 mg/l.

Table 1. PSO made-easy algorithm for assessing river health status

ALGORITHM 1. PSO-made easy model for assessing river water health status

INPUT: Water parameters captured from a river
OUTPUT: optimal p*best* and *gbest* of the rivers

STEP 1: Initialization $c_1=0$, $c_2=c_3=2$, $u_1=0.2$, $u_2=0.4$, $u_3=0.3$, $r_1=0.73$, $r_2=0.25$
STEP 2: Set iteration $t=0$
STEP 3: particles positions $x_i^0, i=1,\dots,n$
STEP 4: particles velocities $v_i^0, i=1,\dots,n$, for $-v_{max}<v_i^0<v_{max}, i=1,\dots,n$
STEP 5: For each particle, assign particle best
$$p_{best,i}^0=\left[p_{best,1}^0=x_1^0,\dots,p_{best,i}^0=x_i^0, i=1,\dots,n\right], f_i^{p_{best}}\left(p_{best,i}^0, i=1,\dots,n\right)$$
STEP 6: For all particles, assign global best $g_{best}=\left\{f_i^{best,i}, i=1,\dots,n\right.$
STEP 7: $t=t+1$
STEP 8: Update particle velocity by $v_i^{t+1}=c_1u_1v_i^t+\left(c_2u_2r_1\left(p_{best,i}-x_i^t\right)\right)+\left(c_3u_3r_2\left(g_{best}-x_i^t\right)\right)$
STEP 9: Update particle position by $x_i^{t+1}=x_i^t+v_i^{t+1}$
STEP 10: Evaluate each particle best
if $f_i^t(x_i^t, i=1,\dots,n)<f_i^{p_{best}}\left(p_{best,i}^{t-1}, i=1,\dots,n\right)$ then
STEP 11: $f_i^{p_{best}}\left(p_{best,i}^t, i=1,\dots,n\right)=f_i^t(x_i^t, i=1,\dots,n)$
STEP 12: else
STEP 13: $f_i^{p_{best}}\left(p_{best,i}^t, i=1,\dots,n\right)=f_i^{p_{best}}\left(p_{best,i}^{t-1}, i=1,\dots,n\right)$
STEP 14: Update global best
$f^{g_{best}}\left(g_{best,i}^t, i=1,\dots,n\right)=\min\left\{f_i^{p_{best}}\left(p_{best,i}^t, i=1,\dots,n\right)\right\}$
STEP 15: if $f^{g_{best}}\left(g_{best,i}^t, i=1,\dots,n\right)<f^{g_{best}}\left(g_{best,i}^{t-1}, i=1,\dots,n\right)$ then
STEP 16: $f^{g_{best}}\left(g_{best,i}^t, i=1,\dots,n\right)=f^{g_{best}}\left(g_{best,i}^t, i=1,\dots,n\right)$
STEP 17: else
STEP 18: $f^{g_{best}}\left(g_{best,i}^t, i=1,\dots,n\right)=f^{g_{best}}\left(g_{best,i}^{t-1}, i=1,\dots,n\right)$

STEP 19: $t=m$ stopping condition is met, display output or go to step 7

3.3 PSO Made-Easy Algorithmic Analysis

We now describe the specific PSO algorithm used in this work. The implementation is an improvement on the standard PSO introduced in [15].

Our approach uses a fully connected topology where nodes are directly connected among each other. This topology is also known as PSO's g_{best} version where all particles in the swarm direct their movement toward the best particle found in the whole swarm. That is

$$g_{best} = min\left\{f_i^{p_{best}}(p^t_{best,i}, i = 1, \ldots, n)\right.$$

PSO's g_{best} is known to converge more rapidly but also susceptible to converge to a local optima [16].

PSO Made-easy algorithm steps. Algorithm 1 in Table 1 presents the steps for the PSO made-easy for assessing river health status.

Step 1 initializes the values c_1, c_2, c_3, u_1, u_2, u_3, r_1, r_2, t (number of iterations), and n swarm size. The values of c_1, c_2, c_3, u_1, u_2, u_3, r_1, r_2 are taken from [17]. Step 3 initializes particle's position, x_i^t, with river water particles values. Step 4 initializes particles velocities using the Newton's laws of motion equations. Step 5 assigns each particle with particle's best position, $p^t_{\text{best,i}} = [p^0_{\text{best,1}} = x^0_1, \ldots, p^t_{\text{best,i}} = x^t_i$, $\text{i} = 1, \ldots, \text{n}], f_i^{p_{\text{best}}}(p^t_{\text{best,i}}, \text{i} = 1, \ldots, \text{n})$. Step 6 assigns a global best for all particles, $g_{\text{best}} = \min\left\{f_i^{p_{\text{best}}}(p^t_{\text{best,i}}, \text{i} = 1, \ldots, \text{n})\right.$. Step 7 increases the iteration number to $t = t + 1$. The particle position is updated in step 8 using equation. Step 9 updates the particle position. Steps 10-13 evaluate each particle best. In our model, the particle best is evaluated by. Steps 14-18 evaluates swarm global best. The process iterates until convergence step 19 or stopping condition is met, or go to step 7.

For PSO made-easy algorithm, particle's velocities are estimated using Newton's law of motion Eqs. 3, 4, and 5.

$$\text{F} = \text{m} \times \text{a}. \tag{3}$$

$$\text{s} = \text{ut} + \frac{1}{2}at^2. \tag{4}$$

$$\text{v} = \frac{\text{distance}}{\text{time}}. \tag{5}$$

Where F represents force, S is measured distance in kilometers from first sampling point to the second and so forth. Acceleration factor a is changes in observed parameter from first sampling point to the second and so forth at time t. initial speed u, initialized to zero.

Water quality index using fuzzy logic. One of the research fields in Artificial Intelligence is fuzzy logic. It is based on mathematics of fuzzy sets [18]. A fuzzy set is defined in terms of membership functions. Membership function of a set is 1 within the

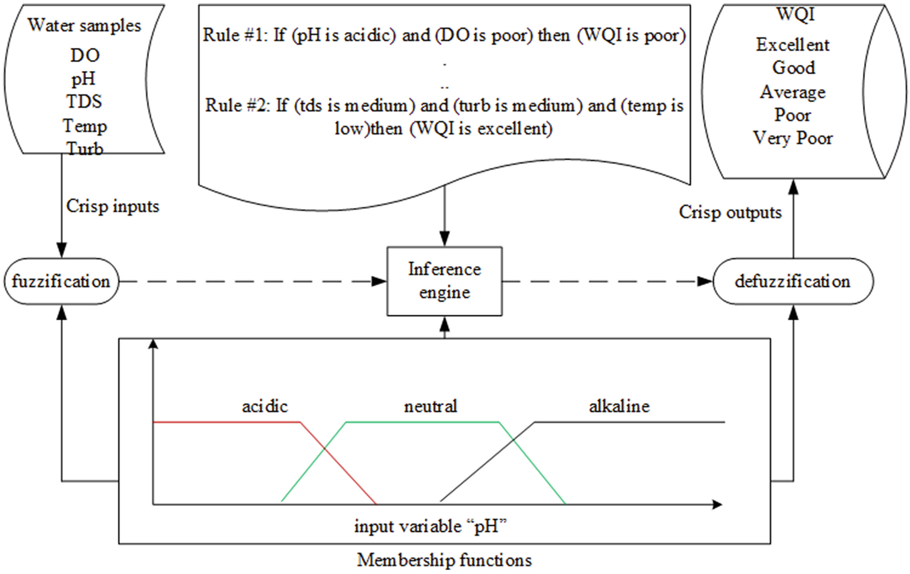

Fig. 3. Different components of the FIS for river water quality index

boundaries of the set and 0 outside. Membership function maps the domain of interest onto the interval (0, 1). The symbol μis used to represent the fuzzy memberships and if x represents the value of sample variable, the μ(x) corresponds to its membership. Fuzzy method utilizes max-min operator to perform fuzzy inference system (FIS) and the standard fuzzy set operations are intersection (AND), complement (NOT), and union (OR).

Fuzzy methodology is developed to propose a new water quality index for Mohokare River. Memberships functions for different water parameters were developed considering boundaries from [14]. Fuzzy inference system was designed to and classifies water quality with membership grade and the components of the FIS are depicted in Fig. 3. To generate membership function, the two pieces of intervals about the same water quality are merged. For example, for pH to be considered as "acidic", pH measurements must fall within [0, 6.5]. For example, for our water quality index assessment using a pH parameter for fuzzy set inputs we have "acidic", "neutral", and "alkaline" and for the output we have "poor", "bad", "average", "good", and "excellent". Trapezoidal membership functions define these fuzzy sets.

In the fuzzy language, it could be:

Rule 1: If (pH is acidic) and (temperature is low) and (turb is bad) and (tds is bad) and (do is bad) then (wqi is very poor).

Rule 2: If (pH is normal) and (temperature is good) and (turb is good) and (tds is good) and (do is good) then (wqi is good).

The last step is defuzzification. The input for defuzzification process is the aggregate output fuzzy set and the output is a single number for each parameter. Parameters included in the fuzzy-based index were selected as key indicators of drinking water quality. These parameters were weighted according to their importance for health implications on human health. Direct weighting factors were assigned to each parameter and the final score was calculated based on these weights.

4 Experimental Evaluations of Mohokare River

4.1 Experimental Setup

Mohokare River (Fig. 4) is an important source of potable water for Maseru City and other industrialized places in Lesotho. It forms an international boundary with the Republic of South Africa in the Free State province. It is about 200 km long. The river faced huge threats from various types of agricultural and industrial activities. In this study, water samples from Mohokare River were collected from four different sampling points as shown in Table 2 in Universal Transverse Mercator (UTM) coordinates.

Fig. 4. Mohokare River, sampling point near Maseru Industrial Site (Yellow flag). (Color figure online)

These sampling points were selected at strategic locations with reference to industries and human activities that are potential sources of pollution to avoid momentary fluctuations in the target parameters because of surface run-off from rain or any other discharges into the river, samples were collected on the same day.

Our implementation platform was carried out on Matlab 2012, a mathematical development environment. The experiment was performed on Windows 8.1 Pro,

Table 2. Font sizes of headings. Table captions should always be positioned *above* the tables.

Sampling Point	UTM Coordinates	
	S	E
1	28.69633	028.23635
2	28.91041	027.89147
3	29.24457	027.54616
4	*29.30662*	027.49146

Intel R Core(TM) i3-2348 M CPU @ 2.30 GHz 2.30 GHz, 4.00 GB Random Access Memory, 64 bit O/S, x64-based processor, 500.00 GB HDD.

4.2 Experiment 1: Assessing the Health Status with Random Initial Distributions

Table 3 presents the water samples parameters captured from four sampling points. Sampling points are represented by x_i, i = 1,.., 4.

Table 3. Measured water samples from Mohokare River.

	pH	Temp.	Turb.	TDS	DO
x_1	7.81	21.2	39.2	0.04	1.98
x_2	7.92	23.5	188	0.08	6.21
x_3	7.94	23.9	946	0.07	5.56
x_4	7.81	25.1	386	0.06	7.21
Min	7.81	21.2	39.2	0.04	1.98
Max	7.94	25.1	946	0.08	7.21

The maximum and minimum values for captured water samples parameters are presented in Table 3 last two rows. Data normalization was calculated using Eq. 6 and the resulting table is shown in Table 4.

$$x_i = \mathrm{Rnd}(x_{\min}, x_{\max}). \tag{6}$$

To estimate particle's velocities, we used Newton's law of motion equations. For example, for pH, from first sampling point to the second, the distance is 40.63 km and the change in pH is 0.11. Using Eq. (4)

$$\begin{aligned} s =& \mathrm{ut} + \left(\frac{1}{2}\right)at^2 \\ =& 0 + \left(\frac{1}{2}\right)(0.11)t^2 \\ =& 40.63 \\ =& 0.055t^2 \end{aligned}$$

Table 4. Normalized data using Eq. (6).

	pH	Temp.	Turb.	TDS	DO
x_1	7.85	24.64	899.09	0.08	3.24
x_2	7.88	21.20	157.32	0.06	4.84
x_3	7.87	24.06	705.75	0.06	5.93
x_4	7.94	23.01	215.04	0.05	5.66

Then

$$t = \sqrt{738.7273}$$
$$t \approx 27.18\text{hours}$$

Using Eq. (6)

$$\begin{aligned} v &= \frac{\text{distance}}{\text{time}} \\ &= \frac{40.63}{27.17954} \\ &= 1.49. \end{aligned}$$

pH velocity from sampling point one to sampling point two is 1.49.

Estimated velocities are presented in Table 5.

Table 5. Estimated particle velocities.

	pH	Temp.	Turb.	TDS	DO
v_1	1.49	6.84	54.98	0.90	9.27
v_2	0.79	3.53	153.50	0.56	4.50
v_3	0.97	2.95	63.70	0.27	3.46
v_4	1.08	4.44	90.73	0.53	5.74

Table 6 shows the minimum and maximum velocities used in normalizing initial particle velocities. Equation 7 is used to normalize velocities as presented in Table 8. The minimum and maximum velocities ensure that during PSO iterations, when velocities change, they fall within that boundary. That is particles are constricted in the range [-min, max] (Table 6).

Table 6. Minimum and Maximum velocities

min	−1.49	−6.84	−153.50	−0.90	−9.27
max	1.49	6.84	153.50	0.90	9.27

$$v_i = \text{Rnd}\left(\frac{-\,v_{max}}{3}, \frac{v_{max}}{3}\right). \tag{7}$$

Table 7. Final velocities obtained by Eq. (7)

	pH	Temp	Turb.	TDS	DO
v_1	−0.07	−1.34	37.40	0.23	−1.45
v_2	0.36	−1.85	−26.21	0.11	2.98
v_3	−0.31	0.95	−0.62	−0.07	1.99
v_4	−0.31	2.25	−9.12	−0.15	2.86

According to algorithm 1, the following steps are performed until all particles converge to a certain value, global best or gbest.

Step 1: Initializes other PSO made-*easy* algorithm parameters by $c_1 = 1$, $c_2 = c_3 = 2; u_1 = 0.2, u_2 = 0.4$, and $u_3 = 0.3$; and $r_1 = 0.73, r_2 = 0.25$. Step 2 sets iteration number to 0. Table 8 shows results of step 3 and 4, initialization of particle position and velocities.

Table 8. Initialization of positions and velocities

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
x_{1i}^0	7.85	24.64	899.09	0.08	3.24
v_{1i}^0	−0.07	−1.34	37.40	0.23	−1.45
x_{2i}^0	7.88	21.29	157.32	0.06	4.84
v_{2i}^0	0.36	−1.85	−26.21	0.11	2.98
x_{3i}^0	7.87	24.06	705.75	0.06	5.93
v_{3i}^0	−0.31	0.96	−0.62	−0.07	1.99
x_{4i}^0	7.94	23.01	215.04	0.05	5.66
v_{4i}^0	−0.31	2.25	−9.12	−0.15	2.86

Table 9. Assigning each particle with p_{best}

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
x_{1i}^1	7.85	24.64	899.09	0.08	3.24
x_{2i}^{12}	7.88	21.29	157.32	0.06	4.84
x_{3i}^1	7.87	24.06	705.75	0.06	5.93
x_{4i}^1	7.94	23.01	215.04	0.05	5.66

Step 5 of the algorithm assigns particle best to each particle in the swarm as shown in Table 9. Step 6 assigns global best for all particles as presented in Table 10 below.

$$G_{\text{best}} = \min\left\{p_{\text{best,i}}^t \text{ where } i = 1, 2, 3, 4, 5\right\}$$

At this stage, PSO iterates to $t = t + 1$ and go to step 8 for velocity updating. This is achieved by step 8 and the updated velocities are shown in Table 11.

Table 10. Finding g_{best}

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
$g_{\text{best,i}}^1$	7.85	21.29	157.32	0.05	3.24

Table 11. Updated particle velocities v_i^{t+1}

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
v_{1i}^1	−0.01	−2.28	−437.58	0.03	−0.29
v_{2i}^1	0.05	−0.37	−5.24	0.02	−0.37
v_{3i}^1	-0.07	-1.47	-329.18	-0.02	-1.22
v_{4i}^1	−0.11	−0.58	−36.46	−0.03	−0.88

In case some velocities moved outside the range, and Eq. 8 is used to clamp them. The algorithm then moves to step 9 for particle position updates and the result are shown in Table 12. It should be noted that after updating, some position fell outside the original maximum and minimum values hence position adjustment was done using

$$x_i^{t+1} = \begin{cases} x_{min} \; if \; x_i^{t+1} < x_{min} \\ x_{max} \; if \; x_i^{t+1} > x_{max} \end{cases}. \tag{8}$$

Table 12. particle position update x_i^{t+1}

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
x_{1i}^1	7.84	22.36	461.50	0.08	2.95
x_{2i}^1	7.88	21.20	152.07	0.04	4.48
x_{3i}^1	7.81	22.59	376.57	0.04	4.71

Table 13. Evaluate current positon with previous position

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
x_{1i}^1	7.84	22.36	461.50	0.08	2.95
x_{2i}^1	7.88	21.20	152.07	0.04	4.48
x_{3i}^1	7.81	22.59	376.57	0.04	4.71
x_{4i}^1	7.82	22.43	178.58	0.04	4.78

Steps 10–13 of the proposed PSO made-easy cater for particle position update and the results are shown in Table 13. Steps 14–18 of the algorithm evaluate the new g_{best} against the previous g_{best} and the updated g_{best} is presented in Table 14 below.

Table 14. Final global bests for each particle

i	1	2	3	4	5
	pH	Temp	Turb.	TDS	DO
$g_{best,i}^1$	7.81	21.20	124.68	0.04	2.69

If the values of x_{1i}^{t+1} do not converge, PSO algorithm increments the iteration number and go to step 8 of the algorithm, otherwise stop the iteration and output the results. The computation continued until convergence. However, it should be noted that not all the particles converged on the same iteration, for example pH and TDS converged at t = 5, temperature at t = 6, O_2 at t = 8 and TDS at t = 14.

Table 15 presents the optimum PSO values for all parameters in Mohokare River. Closely looking at the values, some of them converged to a known value for example pH, temperature, and Total dissolved solids all converged to the same values as measured. However, that is not the case with turbidity and dissolved oxygen since they converged to new values, 124.68 and 2.69 respectively.

4.3 Experiment 2: Deriving the Consensus Health Status

Figures (5, 6, 7, 8 and 9) shows the PSO iteration against the measured water parameters. In all the figures, on the legend, sp 1, sp 2, sp 3, and sp 4 means sampling points 1, 2, 3, and 4 respectively. All the graphs reveal how each particle at each sampling point converges to the optimum value, global best. Figure 5 shows the pH graph for all 4 sampling points and how pH converges at each point. Carefully looking at the graph, we observe that at iteration number 3, all sampling points' values started coming to a single value. Figure 6 shows how temperature for each sampling point performs.

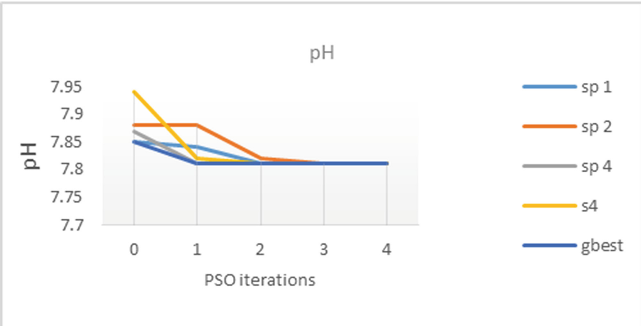

Fig. 5. pH Sampling points convergence vs gbest

Observation on the graph shows temperature coming close to a single value at iteration number 4. Figure 7 presents how turbidity behaves as iterations increase. This particle took much iteration to converge than other parameters. At iteration number 15, we observe turbidity coming to optima. Total dissolved solids (TDS) convergence graph is shown in Fig. 8. TDS converged to 0.04 mg/l at iteration number 4. Figure 9 shows the convergence of dissolved oxygen (DO) parameter for all sampling points.

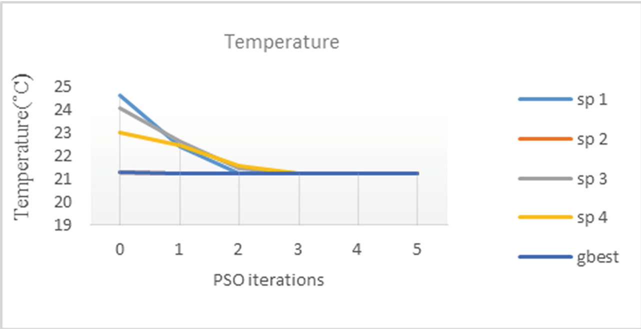

Fig. 6. Temperature sampling points convergence vs gbest

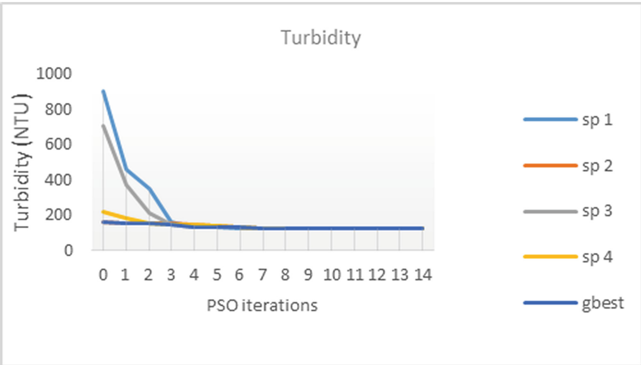

Fig. 7. Turbidity sampling points convergence vs gbest

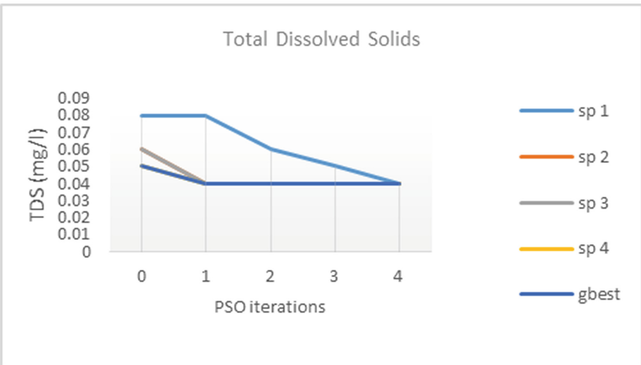

Fig. 8. TDS sampling points convergence vs gbest

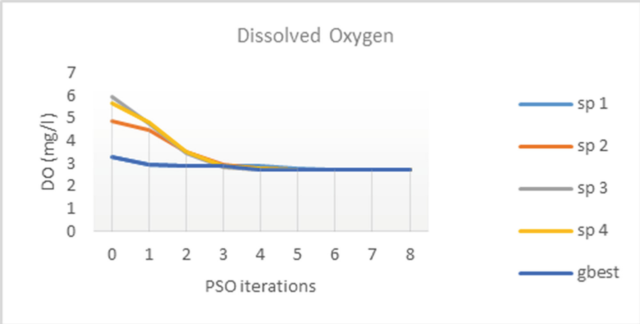

Fig. 9. DO sampling points convergence vs gbest

Looking at the graph, DO converged to 2.69 mg/l at iteration number 6.

Fuzzy inference system was proposed to get the overall health status of Mohokare River. In this study, five quality parameters were included in the index based on their importance including pH, temperature, turbidity, total dissolved solids (TDS), and dissolved oxygen (DO) were used as inputs and WQI as the output. The five water quality parameters were divided into different categories, and trapezoidal membership functions were assigned to each. Ranges for fuzzy sets were based on World Health Organization (WHO) standards. WQI is a 100-point index divided into several ranges corresponding to the general terms as shown in Table 15.

Table 15. Water Quality Index Legend [14].

Quality	Very Poor	Bad	Average	Good	Excellent
Range	7.81	21.20	124.68	0.04	2.69

Figure 10 below shows a graphical algorithmic flow developed for fuzzy logic process where individual quality variables are processed by inference system producing different groups. As per classification, 3 parameters from optimal PSO made-easy global best values were kept in group 1, 2 parameters were kept in group 2. The two groups were combined by keeping physical parameters together and chemical parameters together. According to Fig. 10, temperature, TDS, and turbidity were combined to output G1, pH and DO were combined to produce G2. Groups G1 and G2 were further combined to form group 3 which was processed through fuzzy rules to

Table 16. Water Quality parameter inputs to FIS.

Parameter	pH	Temp	Turb	TDS	DO
Value taken	7.81	21.20	124.68	0.04	2.69

produce overall river health status. Table 16 presents optimal representative values serving as inputs to the FIS.

Following are two sample rules designed for physico-chemical water quality parameters.

Rule 1: if (pH = 7.81, "basic", it implies good water quality) & (DO = 2.69," good", implies good water quality) then (according to Table 17 WQI is good).

Rule 2: if (temp = 21.20, "average", implies good water quality) & (TDS = 0.04, "good", implies good water quality) & (turb = 124.68, "good", implies good water quality) then according to Table 17, WQI = 50, "average").

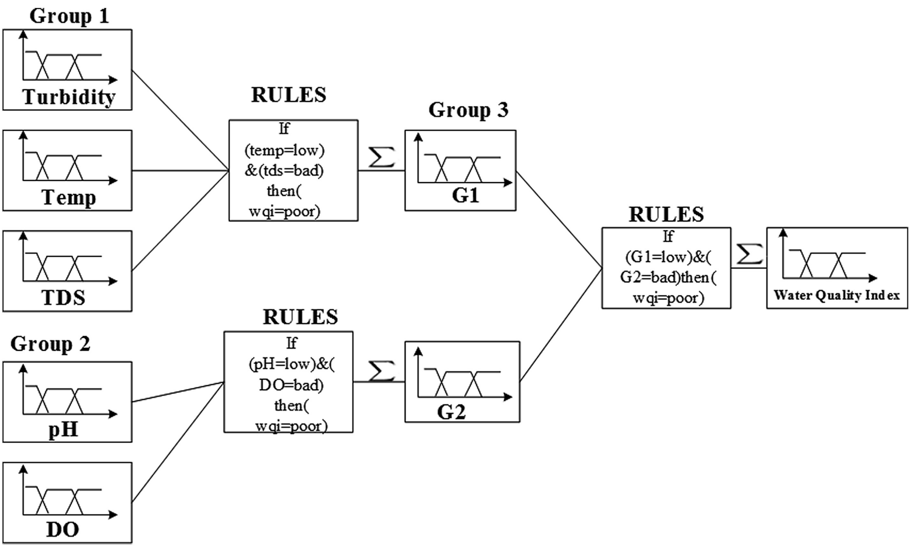

Fig. 10. Graphic flow Fuzzy Process

According to Table 17, the WQI in Mohokare River was found to be in the 50–70 scale. In order to validate the results of the proposed framework, comparison was made with [19] where most river samples showed increasing trend especially around factories. The WQI also showed to be worsening downstream of agricultural farms and urban settlements downstream of wastewater treatment plant.

4.4 Comparing the Proposed Ubiquitous Network PSO Made-Easy with Other Classical Methods

Table 17 compares our proposed model to other related works in river quality modeling. The major concern in river water quality monitoring is the accuracy, timely, and reliable information in order to avoid disaster.

The method proposed in [20] presented water quality on a single point rather than other places where there are also potential pollution sources. In [4], few parameters

Table 17. Comparison of the proposed model with Field-to-Laboratory Models

Proposed Model/ Related methods	Problem addressed	Method	Result	Limitations
Physico-Chemical Assessment of Pollution in the Caledon River Around Maseru City [20]	Automatic calibration of river water system.	CE-Qual and principal component analysis	Experimental results show that their method produced good results. Details in [20]	The complexity increase in the system could the computational and memory requirements for large number of function evaluation may restrict performance hence computational burden.
Monitoring and assessment of water health quality in the Tajan River, Iran using Physico-chemical, fish, and macroinvertebrates indices [6]	Assessment of river water in the Tajan River, Iran.	Measured data on biotic and abiotic elements were used. GIS, univariate, and Multivariate statistics have been used to assess the correlation between biological and environmental endpoints.	Results showed that ecological condition and water quality were reduced from upstream to downstream. Reduced water quality was better revealed by biotic indices than abiotic indices. Details in [6]	Though the proposed method seem promising, it takes a longer time to do the analysis before the results can be published especially in a country like Iran which is located in a mid-dry area where resource management is particularly urgent and important.
Assessment of Water Quality of Bennithora River in Karnataka through Multivariate Analysis [4]	Karnataka River water quality assessment	Multivariate analysis with laboratory experiments and principal component analysis	Results showed that there is potential in improving the efficiency and economy of the monitoring network. Analysis	One-year mean values of water quality parameters were used and prior to making any critical decision in

(*Continued*)

Table 17. (*Continued*)

Proposed Model/ Related methods	Problem addressed	Method	Result	Limitations
			further showed there is potential in reducing water quality parameters. Details in [4]	eliminating water quality parameters, the PCA with longer time scale should be performed. Principal factor analysis is also needed to identify important parameters
Proposed model	Assessing river water quality	Real-time ubiquitous network and swarm intelligence	Experimental results show that proposed model obtain satisfactory results as shown in Sect. 4	Experimental results show that proposed model obtain satisfactory results as shown in Sect. 4

were chosen to assess the river quality making it difficult to judge the quality of water in that river since water quality index is based many parameters. The study presented in [6] provides an assessment and comparison of biotic and abiotic indices based approach for river water quality. Furthermore, authors could not claim that their proposed choice of indices will work in other regions. Compared to other classical models in assessing water quality of Mohokare River [19], the proposed model produced better results in a shortest time. In [19], quality of Mohokare River showed to be worsening especially downstream of garments factories and wastewater plants. The proposed model transmitted data on water quality parameters faster and reduced time-consuming fieldwork. The PSO-made easy algorithm converged after a few iterations. Furthermore, the proposed model proved to be economically since it does not require laboratory experiments.

5 Conclusion

Literature survey indicates that several researchers introduced modern techniques in assessing river water quality. This work presents the design, implementation and evaluation of ubiquitous PSO made-easy framework for assessing river health status through e-Services. The aim of the framework is to ensure real-time water data capturing and water quality assessment using PSO made-easy algorithm to address the drawbacks of the traditional methods of water assessment. The proposed framework showed the flow of data from capturing devices in a river to a PSO made-easy analysis system. Furthermore, the experiment showed PSO model calculations from start to finish. The model was experimented to assess water health status of a Suburban river. The results showed that ubiquitous PSO made-easy framework could be used as a tool for finding solutions to real-world optimization problems such as air quality monitoring, earthquake warnings, tracking health indicators and treatments. The proposed model produced good results because it is better, faster, and economically sound hence the model could be extended to distributed river networks.

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