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Prognosis of urban environs using time series analysis for preventing overexploitation using artificial intelligence

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Abstract: In the process of urban environment, the optimisation of network enactment is shifted from operation to maintenance and monitoring stage. During such conversion it is necessary to indicate the time series representation for preventing the overexploitation problem that happens due to more number of natural resources. It is necessary to use a set of historical data to check the behaviour of current state operations at varying time periods using an intelligent optimiser. Thus this study explores the implementation of time series analysis using artificial intelligence (AI) where accurate predictions are made in the entire urban environment even with big edifices. The major difference that is observed in the proposed method as compared to existing method is that two different boundary regions are chosen with distinct point values and only in two directions the monitoring device is installed. Since AI is involved in the entire process entire characteristics on forecasting current state procedure is represented using modified evolutionary optimisation (MEO) which observes entire biological nature of neighbouring environs. Additionally comparison analysis is made using MATLAB with five case studies where the proposed method proves to be much effective for about 70% as compared to existing models.

Keywords: time series; urban environment; artificial intelligence; AI; forecast.

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1 Introduction

In the entire life time of humans all the natural resources that are present in the surrounding environments are much important. In the absence of natural resources it is much difficult to survive in real-time environment. Therefore, the process of overexploitation which leads to reduction in number of valuable resources must be continuously monitored in order to prevent the life of many individuals. Moreover it is essential to check the rate of natural resources in the environment using an advanced technology. Hence the choice of automated algorithms using evolutionary optimisation that provides appropriate implementation and detection strategies are chosen. Further the optimisation algorithm is applied with the help of network signals that extends the support using satellite devices where all environmental conditions can be monitored. But in proposed method determinations are made for urban environments as the natural resources are decayed in larger amount as compared to rural environmental areas. In addition, many countries have implemented the approach of automatic monitoring where if more resources are exploited then information will be directly transmitted to corresponding agencies thus immediate actions are taken. The proposed approach provides the platform for such monitoring systems where at appropriate time periods stringent actions are taken. Figure 1 provides the block diagram of proposed method for monitoring urban environments using time series representations.

The review of literature is usually carried out to examine the benefits and drawbacks of previous methods with the same methodology. All the observed drawbacks are solved using the proposed formulations to some degree, thus making real-time experimentation

case studies. Also there are different urban environmental factors that usually depend on dissimilar environmental conditions and changes. But all are examined under same similarity condition thus making this section to completely understand the needs of proposed method. In Al-Hourani and Guvenc (2021), a loss model is designed with satellite system with proper path planning conditions where the analytic approach is carried out using perceptible tools. The special tool that is used for the approach is much simple and it increases the accuracy of measurements with a separate receiver systems. However the drawback of the incorporated tool is that if signals are transmitted in huge populated urban areas then tracking a particular receiving station is much difficult thus the path loss is observed to be much higher than minimum values. To control the loss of signal which is termed as avoidance of departed computation more number of sensors are used in the detection process (Takeyama et al., 2017). As a result of combining multiple sensors in a single point of view the error that is present in the signal transmission is reduced to one fourth as compared to original indicated results. Even though the transmission is reduced and low cost is detected a separate pattern for unique recognition of areas are created thus making the process much difficult to tolerate poor reception of signals.

To avoid the signal transmission technique an alternate method is suggested (Wang et al., 2021) using map-based image structure. In this map structure high resolution images are directly fed in to the system using some extractive units thus satisfying the ratio of quantitative and qualitative mixtures. But the satellite images can be used with certain limitations in the observed areas for identifying all objects that overexploits the usage of natural resources. Further the application of satellite images are directly tested for traffic conjecture thus controlling the amount of polluted gas in the entire system (Zhang et al., 2019). For the abovementioned control process big data is preferred with multivariate algorithm which extends the data to further extent for future prediction strategies. Nevertheless the model is implemented anywhere in developed nations thus the success rate of the system is unknown in the application state. On the other hand if the designed system is implemented in real-time then the state of system will achieve high efficiency and all the changes can be tracked immediately without any delay in the entire system.

To reduce the delay an approach on time series is considered with forecast behaviour which is applied for detecting air pollution in small urban areas (Kshirsagar et al., 2022). During this forecast behaviour three factors and their components are used where collision between different structure states are avoided. In spite of two advantages the forecast behaviour makes the system only to observe a rough usage on the data without any stabilisation segments thus accuracy of the connected system is reduced. Moreover a mathematical model is built using simple structure for observing the changes in time series (Padmaja et al., 2021) where a logistic growth algorithm is applied in direct mode. Due to direct model of optimisation a growth factor is represented using multivariate expressions thus a time dependent solution is achieved at end state. Consequently the problem in multivariate communication is that non-linear differential equation can only be designed thus raising the possibility of high threshold effect. Hence to avoid non-linear equations a multiple time series is used that is used for transmitting different signals at distinct time standards (Hajmohammadi and Heydecker, 2021). The aforementioned multiple series time is tested in 30 different countries for controlling the presence of air pollution in entire city. Though some new policies for control strategies must be enabled in the system to detect the daily changing trends using a cross-validation

approach which is never possible to follow. Even some of the changes happened in prior days in the presence of global warming which is highly intensified at heat island areas (Wang et al., 2019). In this real-time cases many observations are made for detecting the correct advert and the only method that assisted many researchers is time series analysis with potential changes in the surrounding system.

Table 1 Comparison of related works

<i>Reference</i>	<i>Evaluation tool</i>	<i>Utilised technique</i>	<i>Performance metrics</i>	<i>Objectives</i>
Awasthi et al. (2022)	-	PSInSAR	Analysing the phase information of permanent scattering candidates	Minimisation of time errors
Benocci et al. (2022)	Soundscape ranking index	Autocorrelation procedure	Sound components at two site references	Minimisation of time errors
Tofighy et al. (2018)	CPU load prediction	Bayesian information criterion	Cloud resource management system with predictions	Maximisation of accuracy
Zheng et al. (2021)	Time series stacks	VIIRS pixels	-	Reshaped urban energy usage
Cao et al. (2021)	Multi-scale time series	Machine learning	-	Minimisation of periodic errors
Proposed	Time series tool	Artificial intelligence	Limitations of weight functionality	Minimisation of overexploitation

The qualities of urban environments are mapped with multiple parametric values by separating a four meter distance value (Nichol and Wong, 2009) where all levels of global information units are plotted. The reason behind this four meter separation is that density and height of the building varies using a local perceptron rule which cannot be applied in any case representative technology. As a result only seasonal variations are found in the representation which is indicated as best indicator for all urban quality environmental factors. Additionally a microwave backscatter data is examined at testing mode of operation with different band of sensors thus establishing a strong correlation (Murugamani et al., 2022) at all three decade factors. But it is not necessary to maintain entire data during the analysis and testing stage as it changes over continuous rotation periods. Apart from simple mathematical calculations efforts are made (Gupta et al., 2018) by building a time series forecasting for urban environments using deep learning procedures. By using deep learning procedure improvement in time series is made at each amount where stage transformations are observed to convert the decomposition rate vector in to normal matrix state. Even many researchers implemented the same procedure with effective traffic handling mechanisms (Marandi and Ghomi, 2016; Al-Bilbisi, 2019; Ennouri et al., 2021; Cristodaro et al., 2017; Bäck and Schwefel, 1993; Li et al., 2010; Zhang et al., 2011) by using distinct mathematical approaches that provides strong particle composition rate. Furthermore the method of generating solid waste is a challenging approach in this type of formulations and it is effectively controlled with twofold crisis format. All the different state of operations are observed and after this careful study the proposed method is designed with proper analytical model as any type of overexploitation can only be avoided if there is proper design and it is followed by optimisation algorithm to increase the efficiency in the design.

1.1 Research gap and motivation

All the existing methods that are used for representing urban environments do not focus on specific outcomes that are related to time series representations. Even few methods that are used for discussing the time series representation addresses the problems that are related to specific environmental resources whereas other resources are not considered in the formulated systems. Moreover the mathematical model of urban time series environment is not provided thus exact outcomes with efficiency is not achieved. In addition the process of overexploitation is monitored in relevance to certain marked points but other unmarked points are left out in certain cases. Hence the gap of overexploitation with time series representation is not grouped in proper order thus providing high degree of drawbacks in the designed systems.

To overcome the above mentioned gap, the proposed method implements a problem formulation approach that provides exact representation of time series with physical representation process. As automated monitoring system using artificial intelligence (AI) is integrated overexploitation of natural resources are established in a tranquil method. Even some additional features in terms of analysis are provided under three different periods thus important changes are observed and indicated using observation points. As random points are marked in the system it is much easier to find the sample set using satellite images thereby providing a clear view with proper construction and maintenance. Furthermore the major gap of testing times using experimental setup is made in urban environments thus real-time outcomes are observed even at high data traffic environments.

1.2 Main contributions

The major objective of the projected method is to observe over exploitation of natural resources that are present at different time periods where it is segmented into three distinct cases as follows:

- The amount of variations in entire system is monitored and if disparities are much higher then inclinations are provided at appropriate points.
- To minimise the amount of errors that occurs at exact marking positions in order to make the identification of points to be much clear for different areas.
- To limit the amount of weight functionalities using AI procedures and to identify both inner and outer boundaries during overexploitation cases.

1.3 Paper organisation

The rest of the paper is structures as follows: Section 2 provides a brief formulated model using time series representation factors and variables. Section 3 integrates the optimisation algorithm with step-by-step implementation case factors. Section 4 provides outcomes of integrated system model for analysing the effect of overexploitation and Section 5 concludes the paper.

2 Analytical design using time series representations

The time series representations are used for determining the amount of over exploited natural resources in the surrounding environment. Therefore there is a need to establish the time series equation for distinct variations in time periods. These distinct variations are observed with respect to equal time periods thus at the output stage entire data will be summed to achieve an optimal value. However the time series representation in urban environment cannot be determined in an easy mode of operation as more amount of population is present in the surroundings. Hence the proposed method is designed to record the status of over exploitation using satellite communication signals where the height of surroundings is calculated by using equation (1) as follows,

$$\sigma_i = \sum_{i=1}^n e^{\left(\frac{h_i}{mean_i}\right)} + n_i \tag{1}$$

where h_i represents the height of board edifices, $mean_i$ indicates the mean values of satellite signals and n_i denotes the noise of satellite signals.

Equation (1) is used for representing the image in three dimensional form whereas the feature vector for determining the time series to find the over manipulation of resources is formulated using equation (2),

$$f_{2D}(i) = \sum_{i=1}^n \begin{bmatrix} c_1 & \dots & c_i \\ \vdots & \ddots & \vdots \\ c_i & \dots & c_n \end{bmatrix} * \begin{bmatrix} I_1 & \dots & I_i \\ \vdots & \ddots & \vdots \\ I_i & \dots & I_n \end{bmatrix} \tag{2}$$

where c_1, \dots, c_i, c_n indicates the calibration matrix and I_1, \dots, I_i, I_n denotes the identity matrix.

The calibration matrix in equation (2) denotes that all the signals that are represented in three different axis is adjusted with central angle and an identity matrix is used for denoting the similarity index. But the similarity index is based on two different image types that is represented in analytical terms as follows,

$$s_i = \frac{1}{n_s} \sum_{i=1}^n image_i * t_i \tag{3}$$

where n_s represents number of similarity index and $image_i, t_i$ indicates the image and training set images.

However the similarity index usually varies using mean observation values that starts at initial period of representation. Therefore the change in time series representation of satellite signals is denoted in mathematical form as follows,

$$t_s(i) = \sum_{i=1}^n t_{initial} - t_m(i) \tag{4}$$

where $t_{initial}, t_m(i)$ represents the initial and mean observation values.

Equation (4) stores all-time series monitored values using difference procedures where at output stage all the series representations are fragmented using equation (5) as follows,

$$t_o(i) = \min \sum_{i=1}^n \alpha_i + \beta_i + \gamma_i \quad (5)$$

where α_i , β_i and γ_i describes the inclination, seasonality and enduring variations.

Equation (5) denotes that decomposition rate of all time periods must be minimised in all axis regions. In order to achieve minimisation in decomposition rate the positioning error of all the measurement system must be minimised using equation (6) as follows,

$$E_{h-v}(i) = \min \sum_{i=1}^n \sqrt{(e_n - r_n) + (e_e - r_e)} \quad (6)$$

where e_n , r_n , e_e , r_e describes the estimated and reference values in north and east axis respectively.

In association with equation (6) the number of observations must be prominent by defining total number of satellite signal control stations in all defined directions. Therefore the control stations with maximum number of observation is established using Equation (7) as follows,

$$observation_i = \frac{1}{s_t(i)} \sum_{i=1}^n (n_a - n_r) \quad (7)$$

where s_t indicates total number of stations; n_a and n_r describes the original and reference observations.

All the designed analytical equations will be formed as a separate loop factor from 1, ..., n and in the next case the algorithmic objective functions will be integrated for optimising the overexploitation characteristics.

3 Optimisation algorithm

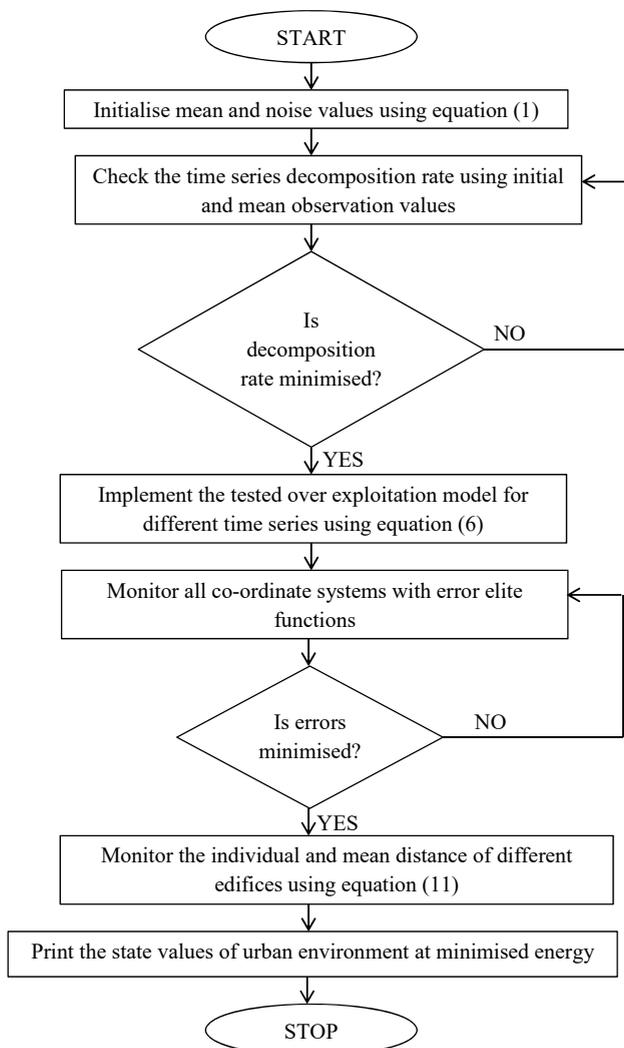
The process of over exploitation can be optimised by using a global algorithm that uses AI as one of the sub-criterion where the same method is computed using soft intelligent techniques. Therefore to control the over exploitation features in the considered environmental factors modified evolutionary optimisation (MEO) is implemented with time series functions. The major advantage of MEO is that it can estimate the characteristics based on biological factors where the error problems are solved in an easy manner. Further the number of parameters that are considered for the optimisation purposed is much lesser thus a natural phenomenon of occurrence is indicated in the entire structure. Moreover even if the population grows higher the fitness functions can be chosen for wide range of problems without any limitation factors. In case if the fitness function is much weaker then it will be immediately removed from the computer aided system and in the next stage more strongly bounded optimisation takes place by filtering all the necessary parametric functions. Additionally there are two different stages of optimisation when MEO is used such as reproduction and transformation. Since the proposed method is based on specific time series in urban environments more importance is given to flexibility in determining the optimal solutions. Hence an evolutionary optimisation technique is needed to adapt them around all overexploited environmental conditions. Moreover high dimensional problems can only be solved using evolutionary optimisation algorithm as compared to other automated algorithms thus reducing the amount of sensitive results in entire process. In addition the proposed method that

monitors the surrounding environments do not need any solution that is approximated for a given factor thus a background function for fitness is created for providing limitations in exploration space. Due to such limitations global solutions are achieved within the expected time series interval. Even as compared to other algorithmic determinations the integrated algorithm provides much low time complexity periods at limited error conditions. The mathematical term representation of the fitness function for two stage are represented as follows,

$$f_i = \sum_{i=1}^n \varepsilon_i * p_i(x) \tag{8}$$

where ε_i indicates the variable parameter and p_i the probability values in the defined functions

Figure 1 Flow chart of MEO with defined objective functions



Equation (8) is used for representing only a single function that corresponds to x . In case of multiple function then functional values can be added. This in turn increases the weigh functionality thus the limitations of weight functions can be determined using equation (9) as follows,

$$w_i = \min \sum_{i=1}^n \frac{n_1 + n_2 + \dots + n_n}{n_r} \tag{9}$$

where $n_1 + n_2 + \dots + n_n$ denotes the inner random values and n_r indicates the total number of random values in outer boundary.

If the weight function in equation (9) is minimised then elite fitness function can be used for representing the factors in MEO as follows,

$$distance_{e_i} = \sum_{i=1}^n \frac{e_i}{e_i + f_i} \tag{10}$$

where e_i indicates the elite functions.

Equation (10) is used for measuring the distance using choice-based technique that is separated by accumulation of elite and fitness function values. Therefore the final evolution values are represented for preventing overexploitation of natural resources using equation (11),

$$G_i = \frac{1}{t_i} |individual_i - m_i| \tag{11}$$

where $individual_i$ and m_i indicates the individual and mutation values.

Equation (11) represents the time series of signals using mutation values where the modulus terms are used for considering both true and false values. The flow chart of MEO with proposed formulation is deliberated in Figure 1.

Algorithm: Modified evolutionary optimisation (MEO)

Input: Initialise fitness function with variable parameters and probability values f_i ($f \leq i \leq n$), $prob_i$ ($prob \leq i \leq n$) and area height of edifices h_i ;

Output: Best control operations for over exploitation in urban environments at maximised population;

Step 1 At first, the objective function is constructed with the set of mean values using $mean_1, \dots, mean_n$;

Step 2 Initialise the calibration and identity matrix that must be followed by two dimensional boundary index b_i with $1 \leq i \leq n$, and its similarity index s_i with the indication of white noise;

Step 3 While ($s_i < N_i$) do.

Provide a complete knowledge on training set images in a systematic way for computing the maximum similarity index by using equation (3);

Verify the value of change in time series using satellite signals $t_s(i)$ for the mean observation values;

If the similarity index is higher s_i is not at ($s_i < N_i$) do

Modify the weight functions using elite values and mutated values that is having different weight functions using equations (10) and (11) e_i with $1 \leq i \leq N$ into N number of mutated values;

```

// Time series phase
Update the time series with inclination and seasoned values using endurance
variations as shown in equation (5);
// Observation phase
Select the number of receiving stations with original and reference
observation parameters  $n_a, n_r$  as defined in equation (7);
Update the modified weights with proper distance values followed by the
overexploitation object tracking mechanism, and compute the error term
 $E_{h \rightarrow}$  as defined in equation (6);
The time series of satellite tracking in all directions is updated by using
equation (4);
 $N_{new} = N_{old} + 1$ ;
End;
Step 4 If ( $\beta_i < 0$ ) then
 $\beta_i \leftarrow 0$ ; // Interchange the existing solution in the current loop with the new solution;
End if;
Step 5 If ( $\alpha_i [0, 1] < \gamma_i$ ) then
Re-initialise the satellite latitude, longitude positions with new segments;
Obtain the overall best solution;
End if;
Step 6 If ( $\beta_i < N$ ) // Existing solution is replaced with the new solution
 $w_{old}(i) = w_{modified}$ ;
 $\beta_i = N$ ; // Attain the most feasible solutions for determining the overall best solution;
Increment the count  $N_{new}$  by 1;
Return the best overall solution;
End;

```

4 Experimental corroboration

The experimental verification for the designed mathematical representation and optimisation algorithm is described in this section and it is used for exact detection of accuracy as compared to existing ones. Moreover the process of preventing over exploitation in surrounding environments can be achieved by constructing a device in hardware segment and all the necessary values are directly fed in to the system for observing varying measurement values. In the proposed method the hardware part is integrated with MATLAB toolbox that is used for providing simulation results for clear observation case. Since the urban environments are wide in nature high amount of storage is provided to the entire system in order to store big data. The entire data at the output is measured as a combined value whereas time series allocation will be provided at the input side for segregating the data. In the experimental verification a causality test is taken at first round and this is indicated as initialisation stage where two different conditions are used in the determination purpose. In addition another major reason for observing the results in computer-based system is that more number of rises are observed

in the urban environment that converts the identification to a difficult one. The comparison that is made with existing model is incorporated with same dataset but the parameters that are used for representing urban environments are modified and introduced in the loop formations. However using the same dataset assures that same case studies are carried out using different optimisation algorithms. In the above mentioned way comparisons are made with one existing model (Wang et al., 2021) to test all framed scenarios thereby all values are plotted using simulation tool. Further the optimisation algorithm that is mentioned in Wang et al. (2021) is incorporated with genetic algorithm where low flexible operations are provided. Even some of the related works in recent times are used for representing time series with two different boundary set but dataset that is implemented usually varies with defined system parameters hence other models and their test cases are neglected. Thus the observation case by using MATLAB is processed using following case studies.

Case study 1: minimisation of system variations

The number of variations from the initial values and time changing measurements is much essential to be observed in urban environment as high amount of natural resources are surrounded in the environment. To examine this case study three variations are considered such as changes due to varying elevation angles, seasonal changes and long-term variations that is denoted by α_i , β_j and γ_k respectively. If any one change is observed then the system will be highly fragmented against environmental factors thus all three necessary variations must be kept as low as possible. Further the most significant factor is seasonal variations in the system whereas time series changes there will be an increase in boundary values. To make this seasonal variation as constant value the mean observation values of urban environment for previous existences must be considered. This in turn adds additional advantage to proposed method as the data collected in the previous set itself determines the possibility of overexploitation in case of natural resources. Figure 2 portrays the possible range of variations in the entire system.

From Figure 2 it is sensible that for the divided time series for disparity of about 200 seconds three distinct variations are observed. But the comparison case with existing method (Wang et al., 2021) is made only for seasonal variations as the much observation and changes needs to be maintained in this particular variations alone. Further all the changes are observed using angle measurement values as exploitation of natural resources changes the content with respect to time series in certain angle periods. Therefore for the time series between 200 to 1,000 the proposed method provides gradient points that are limited within 10 degrees. Whereas the compared seasonal variations indicates that proposed method provides only small change in over exploitation case and in big time series it will be neglected completely. Furthermore the enduring angle remains between inclination and seasonal changes in the system thus proving that more amount of natural resources are saved in the entire time series from urban areas.

Case study 2: reduction of positioning errors

The monitoring device that is involved in the process of avoiding over exploitation of natural resources must be always positioned without any error (i.e.) proper location and installation must be examined in the pre-installation stage. This type of error usually provides high problem to all the urban areas as it is installed in heavily populated areas

that provides huge disturbance. Even due to raising number of buildings it is essential to remove it completely from the system therefore the connection must be completed in an appropriate manner. In a common mode the connections are processed by taking two different directions thus in the proposed method north and east directions are considered. Also the pointing is done at both horizontal and vertical line of axis where the reference values are already fed in to the central system. The reference values include the errors that are observed at previous state of operation (the previous year error reports) and the estimated value indicates the current state errors. The observed error values are plotted in Figure 3 after careful set up is made in two directions. Figure 3 portrays that abnormal positions are placed for some monitoring devices as it is caused due to several factors such as failure to discern proper axis directions, not properly fitting the reference values, etc.

Figure 2 Observed variations with time series (see online version for colours)

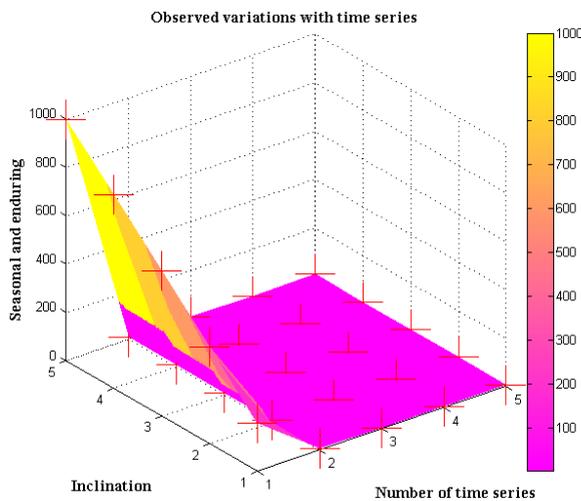
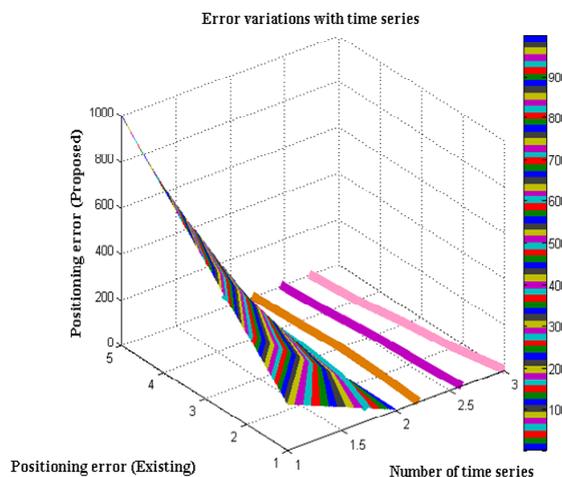


Figure 3 Positioning errors at directional periods (see online version for colours)



Thus to monitor the errors in accurate way the time series is deliberated at an interval between 200 to 1000 where low positioning errors (in percentage) is provided by proposed method as compared to existing model (Wang et al., 2021). Even as the time series increases the optimisation with MEO reduces the error to 0.3 percentage which is much lower than expected error values. In addition at the starting period of time series the position of expedient is not at suitable position thus providing error value greater than 1. Typically the error values must always be less than 1 to avoid improper measurements and this is guaranteed in proposed method as for high time series other optimisation increases the error values and maintains the same until its last position.

Case study 3: limitations in weight functionality

The probability of installation which is measured in terms of weigh functions with two distinct boundaries is calculated in this case study. It is redundant that if multiple functions are stated in a single point during the monitoring stage then due to increased weight functionality the system fails to provide appropriate functional values. Therefore to avoid failure of such systems the weights are divided in the process using inner and outer boundaries with n dissimilar points. In case if there are five points in the outer boundary some additional points will be placed inside the inner boundary as high preference will be given for urban areas that is located in close proximity. Since the outer boundary is having only low edifices it is well known that natural resources cannot be exploited in much big content. Thus it is better to use the monitoring ruse in the inner boundary with high number of points and the total values can be measured by distributing the values at defined precincts. The distributed values are simulated in Figure 4 with comparison avowals.

From Figure 4 it is perceived that weight functions are separated and comparison is made for urban areas. To simplify the simulation the inner and outer boundaries are set with equal values which are equal to 5 but the outer boundary region is again fed into the loop as inner boundary due to reduction is defined set values. Therefore five inner boundary points with one additionally added outer boundary is affirmed for calculating the total weight function. For the defined limits $\{2.4, 3.5\}$, $\{3.5, 4.2\}$, $\{4.2, 5\}$, $\{5, 6.8\}$ and $\{6.8, 7.4\}$ the projected method with MEO provides low weigh function as compared with existing model (Wang et al., 2021) with same boundaries. It can be clearly detected from third set of limit which is equal to $\{4.2, 5\}$ where the weight drops below the negligible amount in projected model which is equal to 0.006 even at heavily populated urban areas. Even though in the same limit the existing method provides small weight function it is not negligible as 0.54 is expanded in the same process.

Case study 4: establishment of elite fitness function

The defined factors in optimisation part using MEO are defined using fitness function where a single figure of merit is achieved for entire population unit. But the problem in the proposed objective function is that two directional methods with two distinct boundaries needs to be defined therefore a set of elite function is considered in the proposed method which provides additional advantage. Moreover an optimal design solution is achieved using fitness function where the applicant solutions are properly defined at input side with best fit at output. Usually the same process is denoted as normalisation of values in other applications but in time series operation only best fitness

value is measured in terms of elite. In addition these elite functions are used for measuring proper distance to make the over exploited signal to reach the central station within the specified time series. Figure 5 specifies the generated elite fitness function with distance measurements.

Figure 4 Weight functions at defined boundaries (see online version for colours)

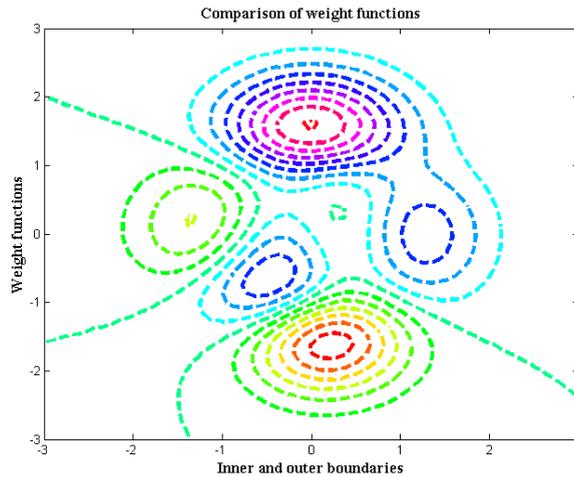
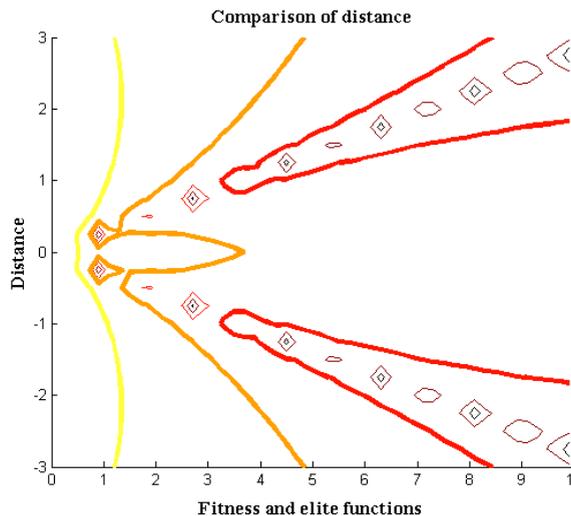


Figure 5 Distance measurement with elite functions (see online version for colours)



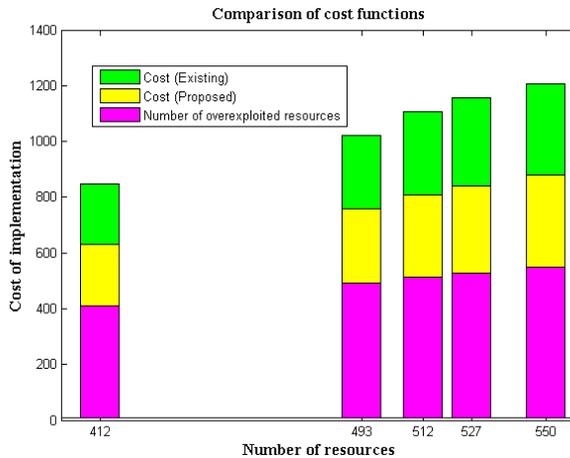
From Figure 5 it is apparent that the fitness function which is represented in red line is reduced in elite terms to reduced functions. In the proposed method the following fitness values 16, 48, 64, 100 and 155 is converted to 8, 12, 16, 25 and 43 where the reduction is indicated in yellow colour line marks. This reduction usually reduces the distance and if it is less than 0.5 then appropriate solutions can be achieved. Therefore the real-time experimentation is carried out for the small fitness function which is equal to 16 and conversion is made in the process. After the conversion the distance of measurement

(during distinct separation) is found to be 0.6 whereas with same adaptation existing model provides 0.8 as distance value. Even with increasing fitness function the distance is minimised in proposed model using MEO as compared to existing method (Wang et al., 2021). For high fitness function values the proposed method adapts itself with defined boundary value to 0.5.

Case study 5: cost of implementation

The cost of implementation for measuring devices is provided in this scenario based on available number of resources. As the urban areas are mostly occupied with high number of resources there is a necessity to change the number of allocated sensing devices which is installed at a single point. Thus cost of implementing the measurable device changes from one region to other and with defined time series. This method of cost calculation provides some insight about non-measurable resources also and during such cases there is a need to replace the entire device. If the entire measuring device is changed then it also involves high cost functionality as the changing prospect cannot be controlled.

Figure 6 Cost function (see online version for colours)



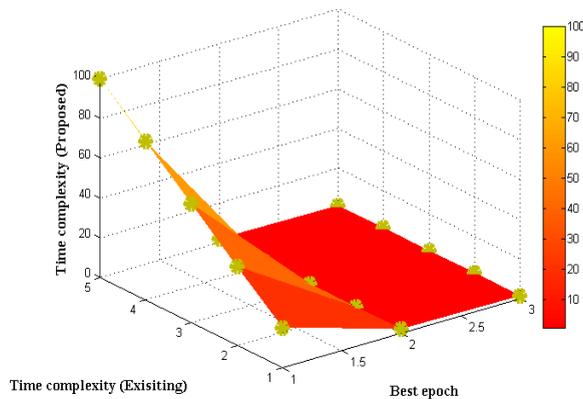
Thus separate regions are analysed carefully and after observing the reference dataset the components for device installation is chosen. At last one mid area with two different resource constraint is chosen and the simulation is indicated in Figure 6. From Figure 6 it is definite that cost of implementation for proposed method is much lesser as compared to existing model (Wang et al., 2021). For demonstrating the substantiation on implementation cost number resources are varied from 3 to 8 where maximum ranges can be extended if more number of resources are found. But in urban areas maximum resources are already kept as eight therefore there is no need to change the system setup in this type of cases. For small number of resources the cost of implementing a single measurable device is 217 dollars in case of proposed method whereas with same resource the existing model provides 412 dollars which is much higher. The same case is observed for allocating high resources which is equal to 8 where 328 dollars are fixed for proposed method and high variations for about 550 dollars are found in implanting existing models.

4.1 Statistical test – time complexity

Since the real-time setup is directly connected with a working tool the time complexity of output periods are observed. In addition the time series representation that is added in the proposed technique will provide some complexities therefore total complexity periods are marked and compared with existing model. Moreover the time complexities describes the amount of time that AI takes to run entire formulated model this time series representation changes at high interval periods. Further in the proposed method many resources are observed and they are separately examined thus total time taken of projected method increases. Figure 7 deliberates time complexities of proposed and existing method.

From Figure 7 it is pragmatic that as number of iteration increases time complexity of proposed method is maximised. For experimental case only best epoch periods are considered in variations of 20 and overexploitation behaviour with time series is demonstrated in the considered periods. During this variation the time complexity of proposed method is much lesser as compared to existing method and this can be proved with best epoch of 60 where total complexity of proposed method is 1.21 seconds whereas for existing method it is 1.94 seconds.

Figure 7 Comparison of time complexities (see online version for colours)



5 Conclusions

The research on urban environments for preventing overexploitation of natural resources which is regarded as growing trend is addressed in this article using AI technique. In this article an analytical model is formulated with newly designed variable that differs with respect to time series analysis. In addition this formulated model is processed using satellite image system that provides accurate solutions with respect to number of natural resources in the system. Further the process is defined using weight functions in two distinct boundary regions in order to separate all the plotted results. A real-time determination is made using the projected model by using three distinct changes such as seasonal, elevation and long-term where the seasonal changes are given foremost important in the entire system. If the seasonal variations are higher then entire system

will result in failure for detecting the amount of natural resources in the urban environment. Moreover the changes are indicated using a set of mean observation values at initial time periods in order to optimise the network to operate at proper urban environmental conditions. The above mentioned observation values indicates that in the proposed system entire network optimisation is directly converted to time series representation model. These types of conversion provide high benefit to the entire monitoring system as entire data can be easily extracted from the system without any interpretation. Even if identical values are found then it is much easier to replace it with current time periods. After careful setup the designed model is tested under five case studies where the outcomes of each case study proves that proposed method is much effective in detecting the over exploitation problems using time series representation. In future the same procedure can be adopted for development of smart monitoring system with the help of automatic robotic systems.

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