Measurement: Sensors 31 (2024) 100980

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

SCMC: Smart city measurement and control process for data security with data mining algorithms

Shitharth Selvarajan [a,*], Hariprasath Manoharan [b], Sonali Goel [c], Chiranjeevi Prakash Akili [d], S. Murugesan [e], Vaishali Joshi [f]

[a] School of Built Environment, Engineering and Computing, Leeds Beckett University, Leeds, LS1 3HE, UK
[b] Department of Electronics and Communication Engineering, Panimalar Engineering College, Poonamallee- 600123, Tamil Nadu, Chennai, India
[c] Department of Electrical Engineering, ITER,SOA Deemed to be University, Bhubaneswar, Odisha, India
[d] Software Engineer, US Technology International Pvt Ltd, India
[e] Department of Computer Science and Engineering, R.M.D Engineering College, Kavaraipettai, 601206, India
[f] School of CSIT, Symbiosis University of Applied Sciences, Indore, India

ARTICLE INFO

Keywords:
Smart city
Sensors
Security
Measurement and control

ABSTRACT

In this paper the importance of monitoring smart city with integration of sensors and Internet of Things (IoT) is discussed with establishment of node control process. To describe the feature of smart cities time measurements are considered with one hop distance between various nodes. Hence the system model is established for various parameters that are integrated with K-means algorithm for clustering and C4.5 for classification. As a result of combining the dual algorithms with system model it is possible to establish a secured state for each data with proper response factor. The major significance of proposed method is to introduce node point where all increasing queues in smart cities are controlled due to the information that is achieved from every data points. Moreover the improvement in projected model can be observed with four scenarios where security at every data point plays an important role at an increased level of 84%. In addition to security the amount of stable points is increased with reduction in disparities for about 2% thereby every applications in smart cities are monitored in a precise way.

1. Introduction

In advanced improvement technologies that are provided with Internet of Things (IoT) all application process can be introduced in standard cities where resources are available for extended usage. If such resources are used for all application monitoring then it is possible to convert the process to smart city where advanced features are enabled. After the combining process of various applications such as healthcare, transportations etc a separate maintenance and control unit must be established to secure the data as big data processing units are involved in the connected systems.

In addition for the established control unit the security of data transmission must be improved by using proper node control techniques that is processed with distance measurements. For all smart cities a separate area of involvement with data classification is provided for increasing the security during data transmissions. On the other hand foremost importance is given to transmitting systems where every data must be transmitted with full unit conversions. Whenever IoT representations are made then all data remains connected in cloud platform hence every data can be accessed by various users under same cluster platform. However for intra cluster regions the maintenance and control points can be extended by segmenting the data with respect to round trip time. Additionally with the use of advanced security sensors a stable control point can be established where queue points are avoided due to round trip time. Hence if the smart cities are monitored with advanced sensors then several disparities that is present in data management system can be removed. Further more the advanced sensors can be connected with real time units where the data can be received with center point representations thus making the smart city sharing process to be flexible than other systems that connects the data management unit for monitoring smart cities. Fig. 1 provides the block diagram of proposed approach.

* Corresponding author.
E-mail addresses: s.selvarajan@leedsbeckett.ac.uk (S. Selvarajan), hari13prasath@gmail.com (H. Manoharan), sonali19881@gmail.com (S. Goel), akilichiranjeeviprakash@gmail.com (C.P. Akili), bsmurugesan@gmail.com (S. Murugesan), Vaishali.joshi22@gmail.com (V. Joshi).

https://doi.org/10.1016/j.measen.2023.100980
Received 6 September 2023; Received in revised form 25 November 2023; Accepted 14 December 2023
Available online 18 December 2023

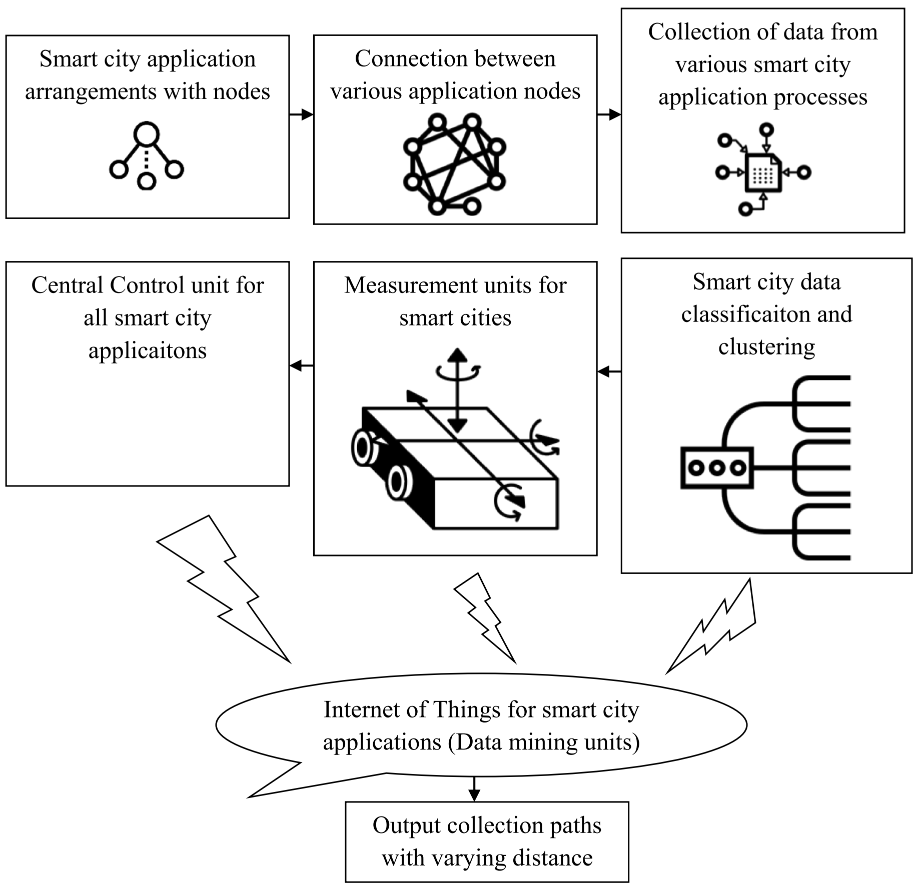

Fig. 1. Block diagram of smart city maintenance and control units.

1.1. Background and related works

All existing works that provides relevant real time outcome examinations with similar design patterns are analyzed in this section in order to observe the drawbacks of conventional methods. One of the main reason for discussing the conventional method is that proper elucidation must be achieved with respect to different parametric analysis therefore achieving accurate smart city solution. In addition to analysis of drawbacks various methods of implementation is also observed with IoT architectures that is built in the top of cross layers for smart cities. In Ref. [1] the security analysis is examined for smart cities only with evolving technologies such as deep learning, advanced classification techniques etc. It is discovered that with deep learning techniques it is possible to achieve a precise solution and new architectures can also be introduced without additional effect. But in real time deep learning algorithms can provide only classification and comparison of various effects for mobility conditions in smart cities thereby it is difficult to achieve precise solutions. Some of the technologies that functions with other classification algorithms are compared in Ref. [2] where decade analysis to observe the challenges in data mining is included. During this type of analysis importance is provided only to sensing units and application layers whereas other parametric elements are not examined which is considered as major drawback. In terms of sustainable development all smart city applications plays an important role where with necessary parameters sustainability is guaranteed [3]. Even though sustainability is assured the way of achieving it must be highly definite for other method implementation. But the way of implementation in other methods does not provide relevant solutions thereby making it practically impossible to be implemented across combined application platform.

Conversely in Ref. [4] a node density platform for smart cities are connected where highly populated regions which are not converted as smart cities are examined by using learning method where IoT is connected for data processing. In all learning models the information about varying nodes are included and if any updates are present then it will be involved to control center. As a result of different parameters node connection update will be provided only to mobile nodes whereas other node information is not present. Additionally advanced models for maximizing the sustainability of various nodes are involved in connection process that suits a particular environment [5]. Whenever a system is designed it must be adaptable to various environments thereby avoiding all external effects with computational technologies involvements for providing improvement is output units. But in the above mentioned case there is no involvement with respect to computational technologies therefore big architectural representations are designed at high cost which is considered as primary weakness. To overcome some of the drawbacks with active involvement of computational technologies it is essential to operate the systems with information gain improvements [6]. If a system is operated with information gain then more number of iterations must be changed in the formed smart city loops thereby creating high clustering units for single application platform. During such formation most of the clusters in smart cities remains unused thus average energy supply is exhausted at no change conditions. Once energy remains wasted then every node can never be connected for proper operation thus leading to additional boosting techniques that are present in deep learning algorithms. To avoid such additional boosting process the system implementation process itself must increase the accuracy by using various classification techniques.

Further it is recommended to follow all communication procedures to search varying solutions for smart cities by using a message queuing protocol where all data is managed with respect to protection schemes [7]. If protection schemes are integrated for smart city monitoring then security of data is assured where controlling of sensors with respect to various data mining is achieved. But with the use of data mining algorithms only clustering and classification problems can be solved and other external control process cannot be provided. Even if control process are determined then a open authorization can only be added with previous contents thus requiring more resources at monitoring state. With such complex involvements entire smart city can never be maintained with maximized life time support. As an alternate to above mentioned methods some of the key performance indicators are determined with respect to advanced algorithms that provides output using specific language units [8].Hence the model driven parameters by using engineering solutions can be achieved in an alternate way thereby every smart city interpretations are avoided. Nevertheless it is possible to avoid complete interpretation from evolution of smart cities but some additional extensions can be evaded. Further more to monitor every smart city with IoT additional resources are needed thereby resources can be shared across different wireless medium [9]. The same process of resource sharing is introduced by various researchers [10] that employ the use of multisource heterogeneous data that is achieved with strategic management systems. Table 1 provides the comparison statement on various methods and algorithms that are used for implementation and monitoring in smart cities.

1.2. Research gap and motivation

There are many existing approaches for monitoring smart cities where solution for problems are provided with many parametric determinations such as energy, distance, accuracy etc. Even some of the recent works that are examined by several researches proved that smart city application process can be monitored with IoT. However the foremost gap that is observed in existing approach is that three objectives such as maintenance, control and security are not analyzed which is considered as major advancement in current generation systems. Hence the proposed method is designed for solving the gap that is present in existing approach where the solution for following queries must be provided.

RG1: Whether the designed system can able to establish proper node control with distance minimization?

RG2: Can the security of data units be maximized with data mining algorithms with appropriate classification and clustering?

RG3: Is the system model flexible for reducing the raising disparities and to maximize the stability of monitoring units?

Table 1
Exiting vs. Proposed.

References	Main characteristics	Objectives			
		A	B	C	D
[11]	Energy management for smart cities using building information systems	✓			✓
[12]	Energy consumption with unique IoT architectures with predictive control		✓	✓	
[13]	Smart city monitoring with cloud computing networks	✓	✓		
[14]	Mapping algorithms for smart city applications	✓		✓	
[15]	Analytic network processing systems for smart cities		✓		✓
[16]	5G for smart cities with energy saving			✓	✓
Proposed	**Maintenance and control of smart cities with data mining algorithms**	✓	✓	✓	✓

A: Node control and time measurements; B: Full data transmission with security; C: Stability and disparities; D: Queue control

1.3. Major contributions

The following parametric objectives must be addressed by data mining algorithms in order to tackle the uncertainties associated with maintaining and managing smart cities.

- By taking into account a hop's worth of distance between two nodes, construct a control point at each node at a different time.
- In order to link secure sensors for data monitoring, entire gearbox units must always be developed.
- To provide the highest level of security at every cluster point, the control centre maintains stability with fewer discrepancies.

1.4. Paper organization

The remaining section of the article is arranged as follows: Section 2 provides the description on designed system model for incorporating security in smart cities using mathematical representations. Section 3 integrates the proposed system model with data mining algorithm in order to maximize the effectiveness of projected approach. Section 4 validates the outcomes of security and data mining algorithm with scenario representations using simulation analysis. Section 5 concludes the paper with directions in future scope.

2. Proposed system model

The measurement and control process for smart cities must be designed in a non-changing way where foremost importance must be provided to analytical representations. Therefore for unique system representations necessary parametric system model is formulated with objective functions that is incorporated for real time examinations. Further the design representations are carried out by considering smart information unit as every control technique is established with data that is processed with IoT. Moreover in proposed system model the control process that represents security that is provided by various sensors that assists smart vehicles for providing clear end-to-end operations.

2.1. Smart city node control

For proper planning and establishment in various cities that needs to be carried out for monitoring purpose nodes must be recognized at all end points in the system. Once the node points are established then several intelligent devices are examined by using a one-hop communication distance as represented in Equation (1).

$$N_c(i) = min\sum_{i=1}^{n} OH_d(i,n) + E_n(i,n) \tag{1}$$

Equation (1) determines the distance control points that converts the signal interaction process in each smart city to be much better as compared to normal interaction process.

2.2. IoT time measurements

If one hop distance communication is established then every IoT monitoring device must complete all data processing measurements at reduced time periods. Hence for short time duration every control process must be highly secured as the system with identical ranges can match at different areas of the city thus leading to data violations. Hence Equation (2) is formulated for IoT data measurement process.

$$TM_i = min\sum_{i=1}^{n} DP_t + PT_t + DA_t \tag{2}$$

Equation (2) determines that for time period measurements every IoT data processing units must be added with effect on different agents that are involved. If the device processing time is much higher then external agents will have much higher effect that maximizes the time period of data transmissions.

2.3. System security

For smart cities the security of IoT data measurements can be observed with authentication process where the system must immediately respond to all data changes. In addition due to involvement of agents it is essential to use a request processing system where the requested data can be transmitted to destination without any delay as indicated in Equation (3).

$$SS_i = max\sum_{i=1}^{n} AU_i + VR_i \rightarrow IoT_d \tag{3}$$

In Equation (3) complete data is measured and controlled with response factor and depending on the response of edge (sensor) devices security of data transmission units are examined.

2.4. Transmitting sensor units

For smart city mentoring and control process full transmission unit must be established by incorporating intelligent sensors within one hop communication distance. The process of full transmission units is defined for each configuration units as consumed energy as formulated in Equation (4).

$$FTU_i = max\sum_{i=1}^{n} (\omega_i \times I_i) + T_i \tag{4}$$

Equation (4) determines that for full transmission units the sensing time period of every node in smart cities must be less than 1 second duration. Conversely the current and voltage units for sensor systems for control process must be established with proper limitations for providing full scale representations.

2.5. Stable control process

After supplying necessary parametric values a stable control process in every sensor must be established in such a way to prevent unsteady flow of two measurement points (i,n). Let us consider the smart city that represent the movement of various medium that are connected with IoT devices for data connectivity.

$$stable_i = max\sum_{i=1}^{n} V_t(i,n)dvdt \tag{5}$$

Equation (5) determines that for every smart medium the stability states must be maximized with time period differentiation. Hence with various medium it is possible to establish constant flow of data.

2.6. Disparity control process

To prevent several raising disparities in smart sensing units it is essential to provide a shortfall estimation of all units. With establishment of shortfall units it is possible to improve smart city structure that helps to control all necessary units without any external agent interpretation. Hence the disparity control process is represented using Equation (6) as follows.

$$DCP_i = min\sum_{i=1}^{n}\frac{u_e + I_e}{A_p(i)} \tag{6}$$

Equation (6) determines the control process with two cycle of energy ranges thereafter utilizing only average power ranges in the system. With control of both energy ranges it is possible to minimize all disparities in smart cities node points.

2.7. Queue control

The smart city information combines more number of units such as vehicular systems, building information, health care, cleaning units etc. Hence for transmitting and storing information more number of sequential queues in the connected system must be minimized as indicated in Equation (7).

$$QC_i = min\sum_{i=1}^{n} AQ_d + VQ_d \tag{7}$$

Equation (7) determines that two types of queues must be controlled as in every smart city virtual units are considered as additional data formations. However actual queues can be controlled by using clustering techniques thereby data rates can be maintained without any variations in reference values.

2.8. Objective functions

All the parametric system model for smart cities are combined as objective functions by using multi objective frameworks with min-max criteria. The objective functions are created in establishing real time outcomes which are directly implemented by using loop formation systems.

$$obj_1 = min\sum_{i=1}^{n} N_c(i), TM_i, DCP_i, QC_i \tag{8}$$

$$obj_2 = max\sum_{i=1}^{n} SS_i, FTU_i, stable_i \tag{9}$$

The objective functions in Equations (8) and (9) is combined with data mining algorithms for classification and training of data units thereby establishing a stability function where end users can configure each units separately.

3. Optimization algorithms

The data mining algorithms that are provided in this section includes a brief overview on both clustering and classification where more amount of sensor data is present. In this type of data mining algorithms it is essential to arrange sensor with page rank matrix thereafter the functionality of each sensor must be defined for smart cities. However in the process of data mining there is a possibility that every item can be grouped based on similarity representations and in further set of sensor monitoring units all similar connectives are removed from the system. Since data mining algorithms can create the reference model in an automated way it is not necessary for defining specific patterns as from the input unit individual architectures can be framed. Additionally if more number of data units is present then architectures can be grouped with sequential representation of individual units. In the above mentioned way every smart city data is incorporated at input where the output architecture can be used for discovering various data in the system. For every designed smart city individual sensing units are connected thus data is transmitted in separate groups after classification with certain labels. Further the data mining algorithms can able to gather only reliable information from available data thus operational unit adjustments are made in case of minor errors. Since the data mining algorithms can able to correct the identified errors all smart city applications functions in an effective way with informed decision making system [17–19]. Furthermore the data mining algorithms can provide additional security by detecting all data threats that is observed after sensing every clustered smart city. Thus the integration process in proposed method is carried out with K-means algorithm for clustering different applications and C4.5 for data classification in to individual architectures.

The foremost advantage of data mining algorithm is that every reliable information can be achieved for smart city applications thereby effective solutions can be accomplished. As compared to other types of data units where smart city applications are built the data mining algorithms are used for finding valuable resources to all nodes that are connected for monitoring purpose. Additionally every user in smart city applications will be informed about decisions therefore it is possible to reduce complete data queues where security of detection is increased.

3.1. K-means algorithm

In the proposed method for smart cities clustering of various paths are needed therefore the value of K is changed several times and in the defined clustering paths necessary applications are involved. If K-means algorithm functions effectively then in the defined clustering paths training period can be provided without any delay which indicates that maintenance and control in all clusters are achieved. At initial state the K-means algorithm defined an initial cluster with 10 independent sub clusters in order to accompany more number of traffic. However once the traffic is accommodated then at remaining clusters the presence of sub clusters will be limited thereby proper maintenance in terms of heavy traffic condition are controlled. In other way the clusters can also be formed as security clusters where in heavy traffic conditions only authorized users inside the cluster regions are allowed to access the data in smart cities [20,21]. The above mentioned process is termed as inter cluster formation and with expanded operations it is also possible to provide intra cluster operation points. Further to provide security for clusters only unlabeled data sets are considered thereby preventing the information of maintenance and control that remains extent across entire network. Conversely as distance is considered as one of the important factor in smart city monitoring and control process, K-means algorithm can support with distance unit formations with established two points (i,n). The major advantage of K-means clustering is that even with more number of clusters the information from different sensing units are transmitted only to central control center therefore it is possible to achieve non-overlapping data to all end users. Another advantage of K-means algorithm in proposed method is that large data sets can be scaled thereby converting the process to be implemented in a simple way.

3.1.1. Cluster focal point

The focal point in the cluster defines the amount of traffic that is present at center point where information at every end is accommodated

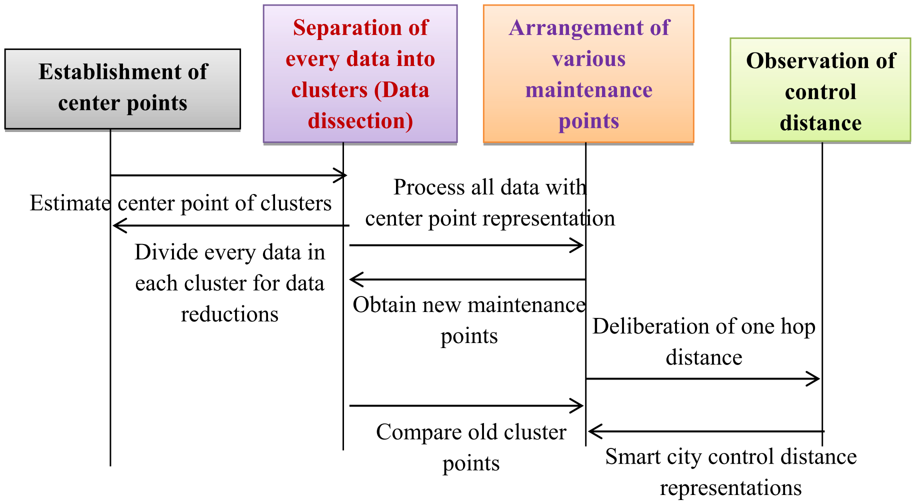

Fig. 2. K-means algorithm for data mining in smart cities.

at control center. Hence more observations must be made with respect to prediction points which are termed as controlling process at mid points. In the proposed method the cluster focal point can be established by using Equation (10) as follows.

$$FP_i = \sum_{i=1}^{n} \beta_i (d_1 + .. + d_i)(\alpha_1 + .. + \alpha_1) \tag{10}$$

Equation (10) determines that established data point at all clusters must be reproduced with center points thereby it is possible to achieve a center point observation for all traffic conditions by preventing number of data failures.

3.1.2. Data center maintenance

With the establishment of various control points a maintenance cluster will be formed as an additional factor in order to monitor every smart city actions. Even though the process of incorporating individual maintenance cluster maximizes the cost of operation a precise maintenance and control with security can be established in this case as denoted in Equation (11).

$$DCM_i = \sum_{i=1}^{n} CL_{new} + CL_{old} \tag{11}$$

Equation (11) represents that in the established cluster itself it is possible to connect a cluster maintenance point thereby minimizing the additional cost of implementation to 50%. Moreover in real time examination on smart cities the maintenance cluster is considered as one of the major importance in the system.

3.1.3. Control distance

For all the operations in smart city a node point distance is measured in order to provide a clear relationship with center point β_i. Moreover the control distance is established in a particular way to locate the nearest cluster center as compared to those with long range points. Further if possibility is there in control point establishments then every cluster can be reformed with distance measurements as indicated in Equation (12).

$$control_d = \sum_{i=1}^{n} (i_1 - i_i)^2 + .. + (n_1 - n_i)^2 \tag{12}$$

Equation (12) determines that if maximum and minimum points in every smart city operations are found then it is much easier to control the data that is spread across the control center.

Algorithm 1.

The step flows of K-means algorithm is provided and block representations are indicated in Fig. 2. Fig. 2 provides a clear description of K-means algorithm where centre points are established in terms of node points thereby every smart city applications are monitored and reported to control centre. Once every data is monitored and reported to control centre then necessary data is transmitted and stored at every cluster thus indicating data partitions have occurred to avoid queue in mining process. Since data partitions are completed for every node there is a need to maintain both new and old node data as it is much important to analyze the changes that are happening in every smart city applications. For every indicated changes amount of distance where node points cannot able to capture the necessary details are observed and in the proposed method to avoid afore mentioned constraint one hop distance is considered.

3.2. C4.5 algorithm

Once the smart cities are clustered then at the next point every clustered units are classified into different set of paths by introducing new architecture representations. The major need of such path classification is to identify the clustered data with labeled set therefore it is flexible for the user to access necessary data in their own authentication way. If entire data about smart cities are classified then a decision tree will be represented in order to choose the best decision that is based on both control and security [22,23]. In case if more number of clusters are providing same decision values with control and security then the precise node can be chosen based on distance. At each cluster node the algorithm selects a subset values which is indicated as sub-tree in order to gain more information knowledge about center control points. The major advantage of choosing C4.5 algorithm for classification is that maximum amount of gain can be achieved after splitting the data in to various segments that are represented by individual class groups. Since C4.5 can be applied with high frequency ranges it is highly suitable for all applications of smart cities where an outlook decision can be taken without involving any external effect. Moreover unlimited paths can be divided with all working nodes therefore it is possible to cluster more number of individual data which varies with center point representations. Further in C4.5 algorithm data over fitting can be avoided for all types of smart data that is present in the output unit. Even if the monitored data by secured sensors are inadequate then C4.5 considers the reference value thereby achieving minimum number of errors at each iteration [22–24]. Conversely for classifying more amount of data the storage space that is provided by C4.5 is much higher as compared to other data mining algorithms.

Algorithm K-means algorithm

Begin PROCEDURE KM

Given

$d_1 + .. + d_i$: Number of data points

$\alpha_1 + .. + \alpha_1$: Total number of clusters

for *i*=1:*n* **do**

1. β_i for identifying center point in defined cluster area
2. FP_i for finding the cluster focal point by using total number of data points

end for

else

for all *i*=1:*n* **do**

3. DCM_i for providing center maintenance point with $control_d$ control point establishments

end for all

end PROCEDURE

3.2.1. Classified data gain

As there is a need in data mining algorithms to select necessary base data for smart city to add as reference values it is essential to determine gain values for further classification or sampling. Hence Equation (13) is formulated for representing the gain of C4.5 algorithm.

$$C4.5_g = \sum_{i=1}^{n} \frac{\gamma_1 + .. + \gamma_i}{\aleph_i} \tag{13}$$

Algorithm C4.5

Begin PROCEDURE C4.5

Given

$\gamma_1 + .. + \gamma_i$: Number of separated data sets

$\aleph_i$: Total number of data branches

for i=1:n **do**

1. $C4.5_g$ for examining the gain of classified data
2. CLI_i for establishing control information over input and information units

end for

else

for all i=1:n **do**

3. acc_i for calculating the accuracy after clustering the available data

end for all

end PROCEDURE

Equation (13) determines that if more number of data sets are divided then gain of transmission system is increased thereby achieving maximum amount of maintenance for all smart city applications.

3.2.2. C4.5 control information

Most of the separated data units must be handled by an individual node where control information is detached across various paths. Hence it is necessary to connect all separated path for measuring control information in C4.5 algorithm as indicated in Equation (14).

$$CLI_i = \sum_{i=1}^{n} \log_2 \frac{Info_i}{Info_t} \tag{14}$$

3.2.3. C4.5 accuracy

In data mining algorithms the accuracy of data information must be improved by a certain factor thus assuring that low errors are present. Hence accuracy of C4.5 is measured with data set and clustering information as indicated in Equation (15).

$$acc_i = \sum_{i=1}^{n} (SED_1 + .. + SED_i) \times CL_d(i) \tag{15}$$

The step flows of C4.5 algorithm is provided and block representations are indicated in Fig. 3. The complete inference for variables in system model and optimizaiton algorithms is provided in Table 2.

Algorithm 2.

4. Results

This part uses hardware and software modules to investigate the integrated outcomes on objective functions with optimization techniques that are introduced for both clustering and classifications. Various sensors that provide security during application integration are connected to a central processor where data sets are saved, and if any modifications are represented with respect to the data, they can be deleted and added in order to validate the results with hardware units. In the smart city monitoring system, multiple reference data sets are gathered from the healthcare and transportation industries, and operational points are defined using values from existing average data sets. More newly produced units are maintained by cloud processing units for the healthcare sector, and changes are managed by data control points to which nodes are connected. The hardware modules also include power supplies that enable the sensing units and node points to function based on a predetermined distance. Additionally, each node and sensing unit is given a round trip time in order to monitor the data within a predetermined timeframe as each user is specified with respect to mobility considerations. Additionally, every characteristic, such as disparity and stability, is tracked using the data set at hand, creating a focal point for numerous clusters. The ideal solution for smart cities can be

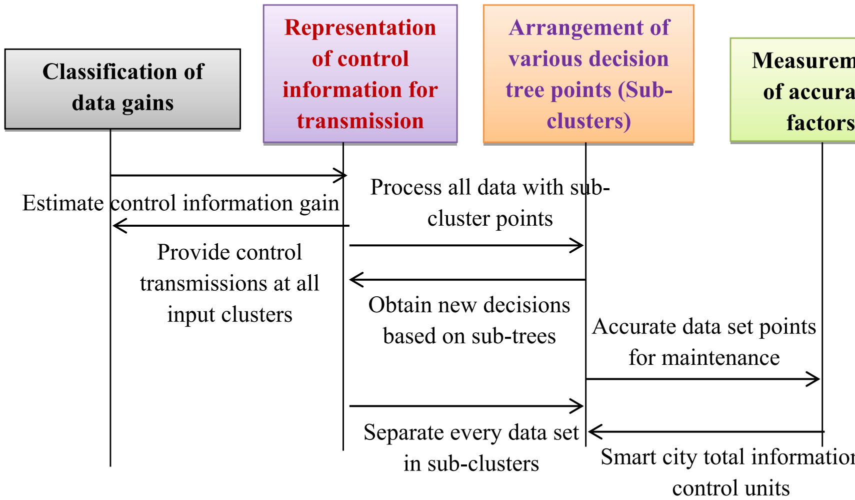

Fig. 3. C4.5 algorithm for data mining in smart cities.

Table 2
Variable representations.

Variables	Inferences
i, n	Measurement points
OH_d	One hop distance
E_n	Edge between two nodes
DP_t, DA_t	Data processing and agent time period
PT_t	Packet transmission time periods
AU_i	Authorization units
VR_i	Validation of data with response factor
ω_i, I_i	Voltage and current for intelligent sensors
T_i	Time period of sensing
V_t	Movement of medium in corresponding time periods
u_e, I_e	Utilized and induced energies
A_p	Average power of each sensors
AQ_d, VQ_d	Actual and virtual queues
β_i	Center points
$d_1 + .. + d_i$	Set of data points
$\alpha_1 + .. + \alpha_1$	Set of clusters
CL_{new}	New maintenance points
CL_{old}	Old cluster points
i_1, i_i, n_1 and n_i	control measurement points
$\aleph_i$	total number of data branches
$\gamma_1 + .. + \gamma_i$	separated data sets
$Info_i$, $Info_t$	input and total information units
$SED_1 + .. + SED_i$	set of data before clustering
CL_d	clustered data set

accomplished in each application by using a variety of data pathways that provide high gain factors, on the other hand, in order to achieve solutions. Every sensing unit in the proposed model has the ability to provide full scale representations, and all input is processed without any data points being rejected. This is the hardware modules main advantage. The following scenarios are executed in order to analyze the proposed system model using optimization algorithms in real time, and the significance of scenario design is indicated in Table 3.

Scenario 1: Node arrangement and time management.
Scenario 2: Secured monitoring and transmission.
Scenario 3: Stable points and reduced disparities.
Scenario 4: Minimization of queues.

4.1. Discussions

In order to run the data constantly with n loop node points, the implemented hardware modules monitored data is transmitted to connected software units utilizing a serial cable connection. The MATLAB IoT toolbox is used to test the software codes in the hardware module, which contains exact replicas of the linked units such as sensors, power supplies, CPUs, etc. connected in a cascaded fashion. The cascaded structure can be extended if more units are introduced, giving software units flexibility for n node representation and allowing for these conversions in the suggested approach as indicated in Table 4.

All the simulation parameters are tested with initial setup that is performed with processor storage units and after a clear examination of working points the outcomes are taken and processed with three dimensional representations. The major reason for three dimensional analysis is that every smart city variations can be observed if a pareto variations with *x,y* and *z* axis representations are made. The detailed description about designed scenarios is as follows.

4.1.1. Scenario 1: Node arrangement and time management

Since security sensors are involved in the process of monitoring systems it is essential to arrange nodes in a particular way that provides extended support for all operations. Hence in this scenario node arrangement observations are processed by considering the installed points. In case if the points are not sufficient then sensing actions will never be provided therefore for monitoring smart cities it is essential to arrange nodes in a proper way. Once the nodes are arranged then time

Table 3
Importance of scenario establishment.

Scenario	Significance
Node arrangement and time management	To arrange all nodes with proper control and at minimized time periods
Secured monitoring and transmission	To increase security of data with full scale transmissions
Stable points and reduced disparities	To establish proper working points for each sensors with reduced inequalities
Minimization of queues	To reduce the data traffic in IoT storage systems and at various nodes

Table 4
Simulation environments.

Bounds	Requirement
Operating systems	Windows 8 and above
Platform	MATLAB and IoT connectivity tool
Version (MATLAB)	2015 and above
Version (IoT connectivity tool)	2.8 and above
Applications	Smart city monitoring for all applications
Implemented data sets	Clustered data with total number of sensors and node points with classified units

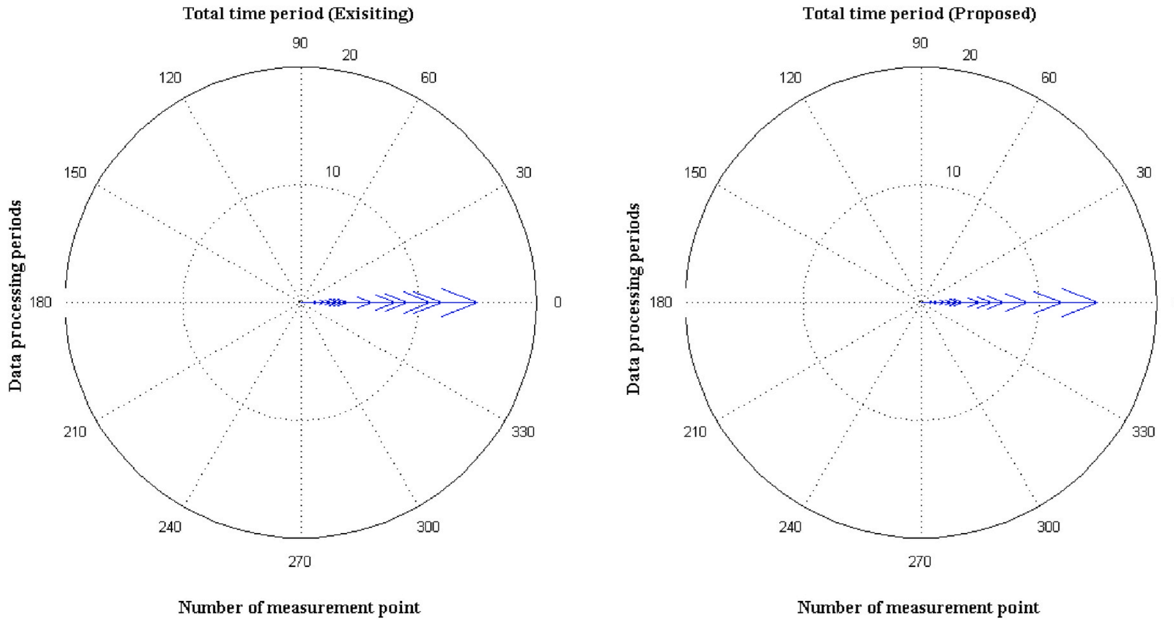

Fig. 4. Total data processing periods for smart cities with varying measurement points.

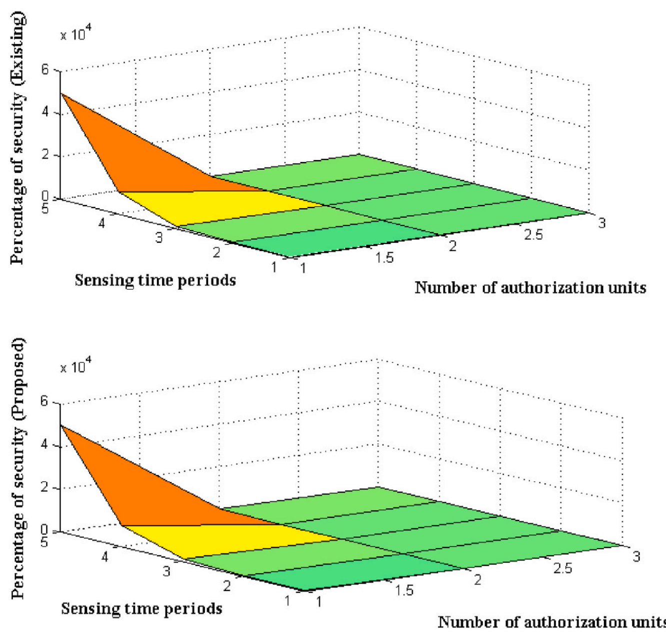

Fig. 5. Number of authorization and secured units with varying time periods.

period of monitoring is checked and reported to control center where if one hop distance is maintained then time states will be minimized. The major problem in distance maximization is that it should support the range of sensors where all edge points must be connected. Hence the node arrangement is measured between two points (*i,n*) by adding both edge and distance points and the time measurement at both the indicated points are observed with data processing, agent and packet transmission times. Fig. 4 illustrates the comparison output for node arrangement and time management process.

From Fig. 4 it is observed that nodes are arranged in a proper way with appropriate time utilization for proposed method as compared to existing approach. The sensors are placed in such a way that connectivity at various points are provided with one hop distance thereby the changes are not made at any edges. However if the sensors are changed then edge point varies and this can be considered only for updated network cases thereafter all edge points can be changed by adding distance points. Moreover with respect to data processing time periods every data is transmitted at initial ranges therefore a minimized time period is achieved. To prove this scenario number of measurement points are considered as 3,6,9,12 and 15 where data processing speed is 1.4,2,2.6,3.1 and 3.5 respectively. For the aforementioned measurement points percentage of node control is maximized to 95% therefore proper information is transmitted at minimized time period of 1 second and 4 s in proposed and existing methods [6] respectively.

4.1.2. Scenario 2: Secured monitoring and transmission

For monitoring entire smart city it is essential the data must be highly secured in all states of application process. Hence in this scenario secured state monitoring is examined with transmission cases where full data transmissions are processed. During secured monitoring state for all

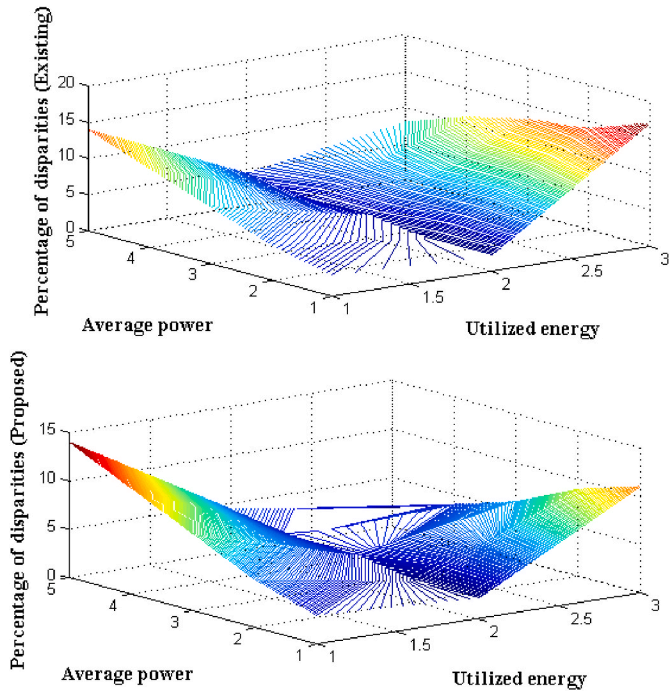

Fig. 6. Expanding disparities control with sensor energy points.

smart cities the data authorizations are maintained separately and during this point the number of valid response from each sensor is observed. In case if data authorizations are much higher with improper valid response then the connected system fails to establish relationship with central controller. But if both authorizations and responses are properly made then appropriate transmission states are maintained. The above mentioned case must also be carried out by checking total number of transmissions where both voltage and current values at input and output units are measured thereby indicating total time period of monitored data. Fig. 5 indicates the comparison outcomes of secured data transmission are both proposed and existing approach.

From Fig. 5 it is obvious that proposed method on monitoring smart cities provides high security and also full data is transmitted as compared to existing approach. The major reason for such increase in security is that number of sensors that are used in the monitoring process for smart cities provides high security thereby maintaining proper control over other procedures that functions without any clustering. Further the full data transmission state can only be established if proper voltage and current values are provided to input unit and in connected sensors both current and voltage values are supplied in a proper way. To prove this scenario number of authorization units are increased from 10 to 50000 in step size of 100, 1000, 10000 where every units are sensed at

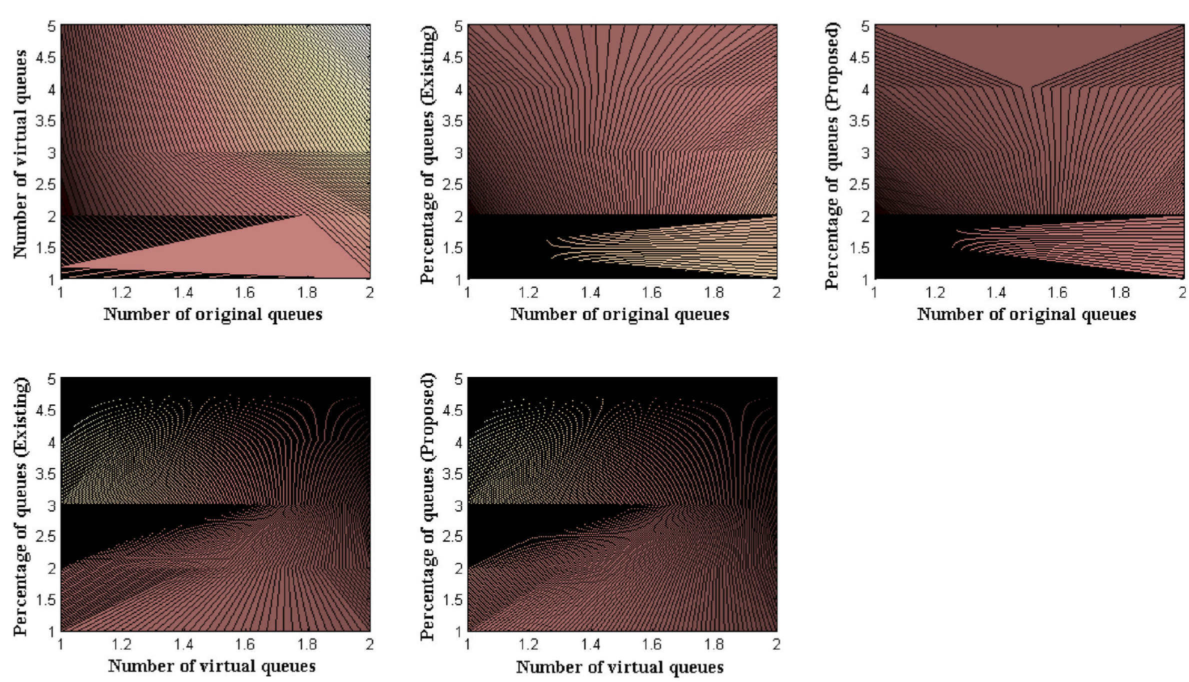

Fig. 7. Original and virtual queues for data rejection point measurements.

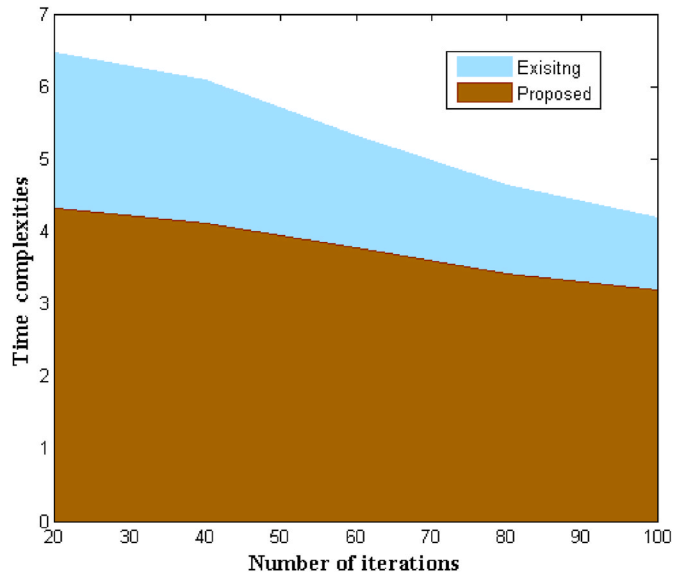

Fig. 8. Time complexities of proposed and existing methods with changing iterations.

50,75,100,125 and 150 min respectively. As a result of such sensing period the percentage of security with full data transmissions is increased to 84% and 53% in case of proposed and existing [6] approaches.

4.1.3. Scenario 3: Stable points and reduced disparities

The smart city monitoring sensors which are connected with data monitoring units must provide stable points thereby reducing the amount of disparities in the connected network. Hence in this scenario number of stable points that provides support for entire operating units are determined by examining the movement with respect to differentiation in time periods. During the process of stable point examination all values at the output will be changed with time periods therefore the procedure of differentiation is considered. In addition the raising disparities must be controlled after differentiation where average power of sensors needs to be examined at this point. Therefore the amount of current and voltage that is supplied for each sensor is added in terms of energy factors where both externally induced and utilized energies are added. The major reason for inducing energies in sensors is that the amount of internally supplied average power is not much enough for operating at different time periods. Fig. 6 provides the simulation outcome of stable points and disparities for proposed and existing approach.

From Fig. 6 it is pragmatic that more number of stable points are established in proposed method as compared to existing approach. Conversely in the proposed method the stable points are achieved in an automatic way without inducing any energy even after time differentiations are made. Due to absence of external energy sources the amount of disparities are also reduced in projected model thus all monitored values for smart city applications provides high functional contents. To verify the real time outcomes utilized energies are considered as 3,5,8,11 and 14 with average power values of 2.13,2.19,3.25,3.33 and 4.46 where in existing method also induced energies considered to be zero. With the above mentioned values the percentage of disparities are found to be 17,14,13,11 and 8 percent in case of existing approach. But in projected model percentage of disparities is much lesser with 11,9,6,4 and 2 percent respectively. As a result of reduced disparities all the smart city applications are operated at high secured rates as compared to existing approach [6].

4.1.4. Scenario 4: Minimization of queues

Even after establishing stable points there is a possibility that the connected networks remains unsafe if more amount of traffic is observed in smart cities for data monitoring process. Hence in this scenario the importance of queue formation and priority among data processing is explained with actual and virtual queue formation systems. In the system model actual queue denotes that for the given number of inputs some queue point will be established which cannot be prevented. Whereas in case of virtual queues if any redundant data is present then it will not be stored in the data storage unit and as an alternative it will be stored in queue. The above mentioned type of storage indicates that a virtual queue is formed due to data rejections thereafter data will remain secured in smart city process. Additionally the rejection process with virtual queues can also be established with priority states where the data that causes more insecure operation can be stored permanentlyin queue units. Fig. 7 demonstrates the percentage of queues for proposed and existing approach.

From Fig. 7 it is obvious that queues are minimized in case of proposed method as compared with existing approach. The number of predetermined queue points is determined to be 500 for both existing and proposed approach before performing real time experimentations. Even though the amount of queue points are lesser the cost of data wastage is reduced and in addition at initial state after smart city monitoring the external data that is not determined by connected sensors are automatically removed from the operating units. To verify the simulation case study number of original queues are considered as 7,10,14,17 and 20 with virtual queues as 56,69,100,114 and 135 respectively. For the above mentioned original and virtual queue values the percentage of queues (data rejections) are found to be 56,69,100,114 and 135. Whereas with same established queue values the percentage of total queues are found to be 43,38,35,30 and 26for existing approach whereas in case of projected model percentage of queues are reduced below 20%.

4.2. Measurement and control: Time complexity

Since the proposed method is based on entire smart city monitoring, various applications will be combined where the time complexity of detection process plays a critical role. Hence in this scenario time complexity is analyzed in addition to time management where the outcomes of smart cities must be achieved at short period of time. The above mentioned outcome can be achieved only if optimization algorithm by using data mining procedures is operated in a proper way which defines that all node points with corresponding data must be achieved frequently at reduced time periods. Further every node points that are connected with clusters must also establish a secured connection with central controller thereafter data separations are made in a proper way. In case if the monitored data for any application is achieved in presence of time complexities then particular data can be removed because it is considered as external attack. Conversely the procedure of minimizing time complexities also attempts to separate the data before clustering thereby achieving high accuracy. Fig. 8 provides the simulation outcome of time complexities for proposed and existing methods.

From Fig. 8 it is observed that due to integration of data mining algorithms the time complexities are reduced as compared to existing approach. To analyze the effect of time complexities ten iterations are considered and a set of combination factor is defined thereby considering the best epoch periods as 20,40,60,80 and 100. In simulation analysis the outcomes are observed for all iterations but the values are present with negligible factors hence only the best epoch values are indicated. The comparison study with existing approach [6] that starts with best epoch of 20 indicates that time complexities remains at 4.73 and 2.14 s. Consequently with increasing epoch periods the time complexities are reduced to 3.19 and 1 second in case of existing and proposed methods respectively. The above mentioned reduced time complexities remains constant even if iterations are increased with more number of nodes and data points therefore a sustainable state can be maintained for every smart city application.

5. Conclusions

The application developments from various sectors that includes transportations, health care etc are combined and represented as major characteristic factors for smart city developments. Therefore for such developments the digital technologies that are connected with advanced monitoring devices provides useful way for introducing wireless monitoring units to long ranges. In addition due to long monitoring ranges with the help of node points it is possible to monitor all smart city application process where data units can be integrated without any external effect. In the proposed method the process of monitoring smart cities are carried out by using various sensors where node control procedures are processed with varying time units. Moreover for monitoring smart cities with sensors data classification and clustering is carried out by using data mining algorithms. Due to incorporation of advanced sensing features the transmitted sensor units can able to achieve solutions in full scale as compared to existing system which indicates that data complexities are reduced. Moreover the smart city monitoring systems must be stable at all established control points where if any disparities are raised then it can be solved with central control unit.

Therefore in the proposed method one hop distance is maintained and with all distance points it is possible to reduce the disparities below 2% thereby achieving a constant smart city monitoring state. The comparative results are taken for four scenarios and a comparison statement is indicated to prove the effectiveness over identical models. For all the scenarios the projected model proves to provide better operating point for smart city applications and it can be proved in terms of achieved real time values. In first scenario the proposed model manages the node effectively for about 95% thereby increasing the security of each node to 84%. In addition high stable points are achieved with reduced disparities of 2% thereafter minimizing the data queues lesser than 20%.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] Q. Chen, W. Wang, F. Wu, S. De, R. Wang, B. Zhang, X. Huang, A survey on an emerging area: deep learning for smart city data, IEEE Trans. Emerg. Top. Comput. Intell. 3 (2019) 392–410, https://doi.org/10.1109/TETCI.2019.2907718.

[2] Shitharth Selvarajan, Hariprasath Manoharan, Celestine Iwendi, Taher Al-Shehari, Muna Al-Razgan, Alfakih Taha, SCBC: smart city monitoring with blockchain using Internet of Things for and neuro fuzzy procedures, Math. Biosci. Eng. 20 (12) (2023) 20828–20851, https://doi.org/10.3934/mbe.2023922.

[3] E.P. Trindade, M.P.F. Hinnig, E.M. da Costa, J.S. Marques, R.C. Bastos, T. Yigitcanlar, Sustainable development of smart cities: a systematic review of the literature, J. Open Innov. Technol. Mark. Complex. 3 (2017), https://doi.org/10.1186/s40852-017-0063-2.

[4] Olfat M. Mirza, Hana Mujlid, Hariprasath Manoharan, et al., Mathematical framework forWearable devices in the internet of things using deep learning, in: Diagnostics, MDPI, 2022, https://doi.org/10.3390/diagnostics12112750.

[5] S. Shitharth, A.M. Alshareef, A.O. Khadidos, et al., A conjugate self-organizing migration (CSOM) and reconciliate multi-agent Markov learning (RMML) based cyborg intelligence mechanism for smart city security, Sci. Rep. 13 (2023), 15681, https://doi.org/10.1038/s41598-023-42257-0.

[6] A. Lestari, Increasing accuracy of C4.5 algorithm using information gain ratio and adaboost for classification of chronic kidney disease, J. Soft Comput. Explor. 1 (2020) 32–38, https://doi.org/10.52465/joscex.v1i1.6.

[7] L. Cruz-Piris, D. Rivera, I. Marsa-Maestre, E. De La Hoz, J.R. Velasco, Access control mechanism for IoT environments based on modelling communication procedures as resources, Sensors (2018) 18, https://doi.org/10.3390/s18030917.

[8] M. De Sanctis, L. Iovino, M.T. Rossi, M. Wimmer, MIKADO: a smart city KPIs assessment modeling framework, Software Syst. Model 21 (2022) 281–309, https://doi.org/10.1007/s10270-021-00907-9.

[9] Q. Yin, G. Liu, Resource scheduling and strategic management of smart cities under the background of digital economy, Complexity (2020) 2020, https://doi.org/10.1155/2020/6624307.

[10] R.M. Soliby, S.S. Jamaian, Non-linearity flux of fractional transport density equation in traffic flow with solutions, Smart Cities 5 (2022) 1655–1669, https://doi.org/10.3390/smartcities5040084.

[11] J. Wang, Optimized mathematical model for energy efficient construction management in smart cities using building information modeling, Strat. Plann. Energy Environ. 41 (2022) 61–80, https://doi.org/10.13052/spee1048-5236.4113.

[12] J. Ke, Y. Qin, B. Wang, S. Yang, H. Wu, H. Yang, X. Zhao, Data-driven predictive control of building energy consumption under the IoT architecture, Wireless Commun. Mobile Comput. 2020 (2020), https://doi.org/10.1155/2020/8849541.

[13] P. Su, Y. Chen, M. Lu, Smart city information processing under internet of things and cloud computing, J. Supercomput. 78 (2022) 3676–3695, https://doi.org/10.1007/s11227-021-03972-5.

[14] Manikandan Thirumalaisamy, Shajahan Basheer, Shitharth Selvarajan, et al., Interaction of secure cloud network and crowd computing for smart city data obfuscation, in: Sensors, MDPI, 2022, https://doi.org/10.3390/s22197169.

[15] C. Huang, S. Nazir, Analyzing and evaluating smart cities for IoT based on use cases using the analytic network process, Mobile Inf. Syst. 2021 (2021), https://doi.org/10.1155/2021/6674479.

[16] M. Humayun, M.S. Alsaqer, N. Jhanjhi, Energy optimization for smart cities using IoT, Appl. Artif. Intell. 36 (2022), https://doi.org/10.1080/08839514.2022.2037255.

[17] Y. Zhang, B. Feng, A. Tian, C. Yu, Z. Liu, H. Zhang, Dynamic transmission rate control for multi-interface IoT devices: a stochastic optimization framework, Wireless Commun. Mobile Comput. 2021 (2021), https://doi.org/10.1155/2021/9974261.

[18] R.V. Kolhe, P. William, P.M. Yawalkar, D.N. Paithankar, A.R. Pabale, Smart city implementation based on Internet of Things integrated with optimization technology, Meas. Sensors. 27 (2023), 100789, https://doi.org/10.1016/j.measen.2023.100789.

[19] D.K. Jang BahadurSaini, S.D. Kamble, R. Shankar, M.R. Kumar, D. Kapila, D. P. Tripathi, A. de, Fractal video compression for IOT-based smart cities applications using motion vector estimation, Meas. Sensors. 26 (2023), 100698, https://doi.org/10.1016/j.measen.2023.100698.

[20] H. Manoharan, S. Shitharth, K. Sangeetha, B.P. Kumar, Measurement : sensors Detection of superfluous in channels using data fusion with wireless sensors and fuzzy interface algorithm, Meas. Sensors. 23 (2022), 100405, https://doi.org/10.1016/j.measen.2022.100405.

[21] B. Chandrakasan, M. Subramanian, H. Manoharan, S. Selvarajan, Original Research Article Future Transportation Computing Model with Trifold Algorithm for Real-Time Multipath Networks, vol. 6, 2023, pp. 1–18, https://doi.org/10.32629/jai.v6i2.618.

[22] S. Shitharth, H. Manoharan, A. Shankar, R.A. Alsowail, S. Pandiaraj, S. A. Edalatpanah, W. Viriyasitavat, Federated learning optimization: a computational blockchain process with offloading analysis to enhance security,

Egypt, Informatics J 24 (2023), 100406, https://doi.org/10.1016/j.eij.2023.100406.

[23] S. Selvarajan, H. Manoharan, A.O. Khadidos, A. Shankar, A.O. Khadidos, E. M. Onyema, Obstacles uncovering system for slender pathways using unmanned aerial vehicles with automatic image localization technique, Int. J. Comput. Intell. Syst. 16 (2023), https://doi.org/10.1007/s44196-023-00344-0.

[24] S. Shitharth, S. Yonbawi, H. Manoharan, S. Alahmari, A. Yafoz, H. Mujlid, Physical stint virtual representation of biomedical signals with wireless sensors using swarm intelligence optimization algorithm, IEEE Sensor. J. 23 (2023) 3870–3877, https://doi.org/10.1109/JSEN.2022.3233407.