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Integration of IoT based routing process for food supply chain management in sustainable smart cities

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ABSTRACT

The rapid growth of population in metropolitan areas has put incremental pressure on urban cities. The centric strategy towards smart cities are expected to cover solution for metropolitan life and ecological environment. One of the significant application areas of IoT in smart cities is the food industry. IoT systems help to monitor, analyze, and manage the real-time food industry in smart cities. In this research, we proposed an IoT based Dynamic Food Supply Chain for Smart Cities which not only ensures the food quality but also provides intelligent vehicle routing as well as tracing sources of contamination in FCM. Furthermore, a smart sensor data collection strategy based on IoT is utilized which would improve the efficiency and accuracy of the supply chain network with the minimized size of dataset and vehicle routing algorithm is introduced and tracing the contamination sources of infected food in the markets. Our proposed model is evaluated with the comprehensive evaluation and used various performance metrics such as tracing accuracy, delay, execution time, and traveling time. The results show that the proposed system outperforms when compared with existing approach.

1. Introduction

In recent years, the development of urban areas have become drastic and expected to be more than 70% of population of the world is going to live in cities within the year 2050. Various challenging problems such as water, supply, infrastructure, constrained energy, and physical space is going to be faced by these cities due to expansion in population. Due to the emerging global markets, competitive environment is increased to ensure the flow of business using the supply chain as the organization firms are not individual and inadequate to this aspect. The supply chain management process the planning, making, deliver, source, and return according to the model known as Supply Chain Operations Reference Model (SCOR) (Jasmi and Fernando, 2018; Maye, 2019). The food supply chain management can be analyzed based on the term items, volume, time, place, price, condition, and correct customer. The network of firms which is known to be supplier networks that upstream on any one firm from the given value system. This network helps in finding the collaboration of firms about the joint output, sales, and delivering of the services or goods that is not depends on a single organization nor following the advancement in supply chain management (de Amorim et al., 2018; Djehdian et al., 2019).

Even with the existing challenges in the development of new technology, the smart cities concept has became the accepted solution for improving the quality of peoples life in urban areas (Chang et al., 2020; Fox et al., 2018). Internet of Things (IoT) plays an important role in the era of supply chain management that has the capability of tracking that no operational cost. Several companies utilized the technology of IoT for the real-time information processing for monitoring the activity of human resources. Due to its novelty, there is no availability of theoretic and systematic framework that can possibly used for the traceability of supply chain perspectives (Ben-Daya et al., 2020; Sharda et al., 2020). Recently, there are several discussion regarding the food supply issues and services in smart cities. However, problems related to food has extremely integrated with the smart cities and making role of food to be one of the important aspects in urban centers. For this reason, smart cities are increasing the practice of developing new methods in

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Fig. 1. Proposed Framework for IoT based Food Supply Chain Network.

preserving the food related social actions and movements from city councils and authorities (Filippini et al., 2019; Sloane and Oreilly, 2013).

It is widely acknowledged that the Internet of Things (IoT) is a new Information Technology (IT) revolution that is causing a paradigm shift in a variety of fields, including supply chain management. The Internet of the future will be made up of heterogeneously connected devices that will further expand the world's borders with physical entities and virtual components (Ben-Daya et al., 2019; Gubbi et al., 2013). Sensor technology advancements and ubiquitous broadband communication have laid the groundwork for IoT. Many of the things that surround us will be on the network in some form or another under the IoT paradigm (Li et al., 2015). IoT that relies on sensors for readings/data collection, in particular, can have a significant impact on the food supply chain. The authors claim that today's food supply chain is extremely distributed and complex, with a large geographical and temporal scale, complex operational processes, and a large number of stakeholders (Hazen et al., 2014). According to them, complexity has caused numerous problems in quality management, operational efficiency, and public food safety. The use of sensors and other IoT-enabled devices in the supply chain of food and perishable goods plays a significant role in generating readings of the conditions pertaining to the goods being transported (Verdouw et al., 2016).

In this research, we focus on two major points in which obtaining the quality of foods will be the first factor and delivering the food within minimum time is the second factor. In order to enhance the food supply management in smart cities, we propose IoT based food supply with dynamic vehicle routing (IFSCDVR) with Bee colony algorithm. This paper categorized into four main sections and these are as follows: Section 2 discuss the related works of the food supply chain and recent trends on smart cities. Section 3 elaborates the proposed methodology for the food supply management in sustainable cities. Section 4 discuss the results obtained using the proposed methodology and finally we concluded with future enhancements in Section 5.

2. Related works

Allam and Newman (2018) underlined the concept of smart cities are still in the improvements stage, historical profiles and cultural values of a city which are considered for development and planning of smart cities. The sustainability core aspect has received less attention in contrast of emerging multidimensional smart cities paradigm. Djehdian et al. (2019) highlighted the Water-Energy-Food (WEF) systems exposure in urban cities to direct and indirect scarcity concerns based on the transboundary scale. The ongoing transitions is reflected by these deliberations upon the implementation of WEF nexus towards the goal of long anticipated resource management integration for considering the temporal and spatial scales. Sloane and Oreilly (2013) discussed the key focus on supplier networks for the organizational firms that related to the stress of smart cities about the use of data that is shared and the technological advancements which becomes increase in the distribution among the companies and also the investment possibilities among the firms and initiatives that affects the trend of smart cities.

Cooper et al. (1997) discussed the revolution of supply chain which reshaping the various industries by reconsidering the activities, organizations, resource flow, and information which involved in the movement of service or product from suppliers to customer as a system. Eksoz et al. (2014) discussed with the challenges about the perishable food industry which should be reconsider the recent operation models for the supply chain and improve the management systems for the betterment of unpredictable situations that meets the quality requirement for the food supply chain. Regattieri et al. (2007) proposed a framework for the traceability of food which consists of product data, routing, traceability tools, and product identification. Authors also discussed the different technologies like radio frequency identification (RFID), bar codes, and alphanumerical codes. Kelepouris et al. (2007) discussed the practical circumstance on usage of RFID in the traceability of food products supply chain.

The modern food supply chain is highly centralized, relying heavily on central powers to regulate data flow. Centralization can jeopardize supply chain transparency, resulting in information inequality and trust issues (Tian, 2017). Companies can choose to open up specific information that benefits their brand image. Companies, on the other hand, can conceal information so that customers only know what food companies and governments want them to know. A centralized supply chain increases the likelihood of being a target of bribery (Mao et al., 2018).

Yan et al. (2012) discussed the importance of supply chain integration for the improvement in coordination of smart cities. Proper exchange of data and agile establishment properties must be indulged with the smart cities which is much needed by the supply chain integration for improving responsiveness. Ying and Fengquan (2013) analyzed the cloud and IoT based technology for agri food supply chain management in the Indian context. They have proved that digitized SCM can improve the accurate and quick delivery of products with minimum time even with the risk management in smart cities. Cardoso et al. (2013) used Mixed Integer Linear Programming (MILP) model for proposing Closed Loop Supply Chain (CLSC) optimization method for designing the supply chain and robustness analysis where the authors compared with several other approaches with the help of variations in the parameters. The capacity expansion facility is modeled together with the demand uncertainty. The major disadvantages of MILP is discussed by Esteves et al. (2012) where the comparison with other approaches have not shown and the problem solved like a fluid and data needed is much larger for the system. Drangert (2021), proposed a combination of two approaches such as flexible water balance and substantially reduce water to access the safe urban water that will hlep in the food nutrients to recover from suburbs which needed in the food production. Sanyal et al. (2021), proposed a game theoretic framework for distributing the surplus food in smart cities. Authors used strategic settings to develop redistribution framework for surplus food that facilitates a smooth exchange between smart cities.

3. Methodology

In this paper, we focus on two points, first the freshness of food quality and second fast delivery in minimum time. Based on this we propose IoT based Food Supply with dynamic vehicle routing (IFSCDVR) using Bee Colony algorithm. The architecture of proposed work is shown in Fig. 1. In this architecture, we consist of a five stage food supply chain (FSC): Food Producer (FP), Food Processing and Packaging Industry (FPPI), Warehouse and Distribution Center (WDC), Supermarket (SM), and Consumer. At each FSC stage we deployed various sensors for measuring and monitoring food quality, safety, and freshness. This sensor sends their information to the Control and Monitoring System (CMS). The CMS collects, aggregates and stores the data in its database and transmits this data to contaminate trace modules at cloud computation. For dynamic vehicles during transportation, we propose Road and Vehicle Network that consist of various road-side sensors deployed at the road side and vehicle sensors equipped with vehicle units.

3.1. IoT based Food Supply Chain Network

3.1.1. Food producer (FP)

At this stage we deployed various IoT sensors at farm land to gather real-time data information of soil and atmosphere. The most common agriculture sensor including optical sensor to sense light intensity, dielectric soil moisture sensor that detect soil moisture level, electrochemical sensor assess ph and nutrient solution level, mechanical sensor sense compactness of the soil, airflow sensor detect permeability of air in the soil, and weather detection unit detect information including temperature, humidity, wind direction, chlorophyll content, wind speed, solar radiation atmospheric pressure, leaf wetness etc. All this real-time data information collected from various sensors are first compiled and sent wirelessly to control and monitoring systems (CMS) at regular intervals of time. We also deployed airborne vehicle sensors to monitor the animal livestock and related monitoring information is sent to CMS periodically. The CMS here refers to the Raspberry Pi Controller whose work is to collect data from farm sensor nodes periodically, and then store, manage, and process this data accurately. This processed data is automatically sent to the web server in real time. This configuration system helps the farmer to keep track of vegetation. This farmer can monitor and control the farming using mobile apps via smartphones, laptop or computer. This mobile app is connected to the web server that sends all the update information of farm land periodically to farmers and helps the farmer in agriculture tactics.

3.1.2. Manufacturing Warehouse Centre (MWC)

The important resources of food are agricultural, fishing and animal livestock. The food product from animal livestock, farming and fishing is considered as raw material and transmitted to the manufacturing industry where food processing and packaging of food products is performed. All this raw material is first sent to the manufacturing warehouse unit and then transmitted to the food processing and packaging industry.

3.1.3. Food processing and packaging industry

Gathered raw materials are then processed in the food processing stage. At this stage also, deployment of configuration of various sensors with control and monitoring system (CMS) is carried out. Food processing is monitored using various sensors including chemical sensor, ph sensor, microbe detector sensor, gas sensor and all these sensors are different levels of food processing. With the help of sensors, we can collect the data about time and temperature during different food processing operations. In addition, with time and temperature, we can also monitor the food quality by sensing ph level during cleaning operation, foreign bodies detection, monitoring of moisture, micro-nutrients, fat and other food components, microbial and chemical contamination, food quality detection based on color, texture, and flavors. This sensing information then timely transmits to CMS where data is processed and transmitted to cloud computing model for tracing and tracking of freshness of food quality is computed and revert back to associated stakeholder via mobile app. Once the food processing with measured food quality is performed then later on packaging of food product is performed. Food packaging unit also deployed sensors during packaging time for tracing and tracking of freshness during packaging and transportation time. Nowadays, nanotechnologies are in trend for food packaging. Nanotechnology enabled nanosensors are used for creating smart tags and smart labels in the form of barcodes, QR codes and RFID tags. Nanosensors equipped with smart tags and labels are layered with recognition particles. They can measure ph and identify pathogens, hydrogen protons, organic molecules (like protein), microorganisms and biological particles. Some of the nan-sensors used for the research are RFID and ripeness indicators. Food packaging integrated with smart nanosensor solutions preserve food-quality, extend the shelf life of food, and monitor food product status. Like food processing, all the sensing information via nanosensor enabled smart barcode and RFID tag sent to CMS, and then sent to cloud computing for tracing and tracking of freshness during packaging and transportation time.

Input: T_p represent type of particular pathogens within food product
Output: sampling-item set

Find probability of infection P_I based on T_p
System Configuration: Network topology data, Number of infection intervals, P_I
Sampling and partitioning a small fraction l using Eq. (1)
TOP=∞
while l≤TOP **do**
  Calculate posterior probability using Eq. (2)
  Combine prior and posterior probability and obtained revised probability using Eq. (3)
  for x=1(Number of Infection Intervals) **do**
    if $Prb.Interval_x \geq TOP$ **then**
      TOP=$Prb.Interval_x$
  if TOP≤85% **then**
    if l≤TOP **then**
      Sample (TOP-1) food products
    else
      Break

Algorithm 1. Bayesian network based dynamic sampling algorithm.

3.1.4. Food supply warehouse and distribution center (FSWDC)

During food supply transportation, distribution, and warehousing, vehicles and pallets are equipped with IoT sensors that detect temperature, humidity, and levels of different gases on timely basis and send the collected data from sensors to CMS and then to warehouses management systems through wireless gateways to allow remote control monitoring and generate alert messages if any abnormality is detected to particular stakeholder via mobile app.

3.1.5. Supermarket

Various sensors for temperature, humidity, and gas level detectors with nanotechnology equipped barcodes and RFID tags are deployed at grocery shelves. This sensor and nanosensors equipped with barcode and RFID tags sense the data regarding pathogens, microorganism, organic molecules, humidity, temperature, levels of different gases, and monitor food product status.

3.1.6. Consumer

RFID and barcode are scanned through Smartphone and consumer can access the freshness of food and other content about the product via smart

3.1.7. Cloud computation

Cloud computation consists of three modules: Contaminate Food Tracer (CFT) module, Vehicle Route Generator module (VRG) and Data Repository and Transmission Module (DRT). From every stage of FCM sensor data sends the sensor information to the cloud via CMS.

3.1.8. Contaminate food tracing and tracking (CFT) module

In this section we proposed Dynamically Partitioned Self-Adaptive Tracing and Tracking (DPSTT) system for sensor efficiency improvement and tracing and tracking of food product. DPSTT system manage the sensor data efficient and detect contaminated food product and source of contamination. DPSTT system is composed of two strategic algorithms: Bayesian network based dynamic sampling algorithm, self-adaptive tracing and tracking algorithm tracking algorithm.

Step 1: Bayesian network based dynamic sampling algorithm:

In this algorithmic step, a bunch of whole food products are sampled and divided into small groups or batch-lots based on the end-market they belong to. The system divides the whole group of foodstuffs into several parts according to the lots they belong to in the end markets. The sampling-item capacity for batch-lot l of supermarket s is computed using Eq. (1):

$$\sharp Samitem_{(s,l)} = \sharp Samitem_{total} \times \frac{\sharp foodstuff\ fs(s,l)}{\sum_{s=0}^{S}\sum_{l=0}^{L}\sharp foodstuffs_{(s,l)}} \tag{1}$$

Where, S represent number of supermarkets and L represent the number of batch-lots in the food chain network. Subscripts (s,l) represent number of sampling-items in batch-lot l of supermarket s, and subscript (total) represent the number of total sampling-items in all batch-lots for all supermarkets. The TOP value represents the network topology data transferred through the system.

Dynamic strategy based on Bayesian estimation is implemented to attain minimal sample capacity. First, we determine the probability of infection of a specific pathogen within the total food product supply chain network then train the model accordingly to obtain the total probability distribution of infection within the total food product and this infection probability is considered as prior probability. The binomial distribution of probability density function is represented as a function of probability of infection intervals. Conversely, posterior probability is the rate of infection obtained by sampling a small fraction of food products. Here we assume f as disease-ridden foodstuffs present within p sampling-items under percentage interval range of infection with prior probability of q_i%, using binomial distribution we determined conditional probability using Eq. (2):

$$Prb(Pr_i) = (pf)q_i^f(1-q_i)^{p-f} = \frac{p!}{f!(p-f)!}q_i^f(1-q_i)^{p-f} \tag{2}$$

Here, Pr_i represent the occurrence infection percentage within whole food product in supply chain network which falls into range of ith interval with q_i% as a prior probability, Ps represent the occurrence of event through which we determine f infected food products in p sampling-items. P_I is the probability of infection.

Next, we combine prior and posterior probability using Bayesian estimation and obtained revised probability that precisely define the infection percentage within food supply network using Eq. (3):

$$Prb(Pr_i|Ps) = \frac{Prb(Ps|Pr_i)Prb(Pr_i)}{\sum_{i=1}^{p}Prb(Ps|Pr_i)Prb(Pr_i)} \tag{3}$$

The pseudo code of this algorithm is shown in Algorithm 1

Step 2: Self-adaptive tracing and tracking algorithm:

After sensing, partitioning and sampling, we add up all the contaminated and uncontaminated food products within the supply network that are passing through every location. These food products are stored with two labels: FRESH and SPOIL for every location and

Input: Product items with sensor and spatial information
Output: Source of contamination
f=0
for i=1:Number of items **do**
  for j=1:Number of (localities/lots on items route path) **do**
    if $item_i$ is contaminated **then**
      $Samitem_i.locality_j.lot_j.SPOIL++$
    else
      $Samitem_i.locality_j.lot_j.FRESH++$
for s=1:Number of (localities/lots in the entire FSC) **do**
  if $locality_s.lot_s.FRESH \leq \omega \&\& locality_s.lot_s.SPOIL \geq 0$ **then**
    Store locality.lot into DOUBT[f]
    f++
Reject DOUBT f
if Number of DOUBT ≥1 **then**
  Find food IDs approved all doubt item
  if Number of ID ≥0 **then**
    Find food IDs approved at least one doubted item
Build DOUBT Tree of lots according to the rout paths of these food IDs
for = 1:Number of Tree Nodes (FSC Entity) **do**
  if $DOUBT[l].locality_l.lot_l.FRESH \leq \omega \&\& doubt[l].locality_l.lot_l.SPOIL \geq 0$ **then**
    source=DOUBT[l]

Algorithm 2. Self adaptive tracing and tracing algorithm.

place. We assume ω as contaminated value based on the total number of samples and probability of infection probability of contaminant source, and we calculated this value using Eq. (4):

$$\omega = \frac{\sharp Samitems \times Prb(Ps)}{\sharp lots} \tag{4}$$

Pseudo code for tracing Algorithms is shown in Algorithm 1. To improve speed and performance of the algorithm we use the DAG tree as a doubt tree and determine the source of contamination. For this first, we exclude food products that are doubted as spoiled having SPOILED value very less. The DFS method mainly used for identifying the root source for the contamination of food supplies. THe DFS traversing will help to traverse the root direction of vehicles. Then create a doubt tree with all doubted lots and localities within the food supply network. Then perform DFS traversing within the doubted tree and pick the node that meets the criteria and identify as the root source for contamination.

3.1.9. Vehicle route generator (VRG) module

The VRG module generates a number of route paths for requested sources and destinations using GPS satellites. With GPS, VRG first finds the road map then splits it into small segments and converts this segment into a graph. Graph G_{RM} can be viewed as nodes (N) and edges (E), for a road network graph set of intersections are considered nodes while the edge between them represents routes. This graph is given in Eq. (5):

$$G_{RM} = (N, E) \tag{5}$$

Based on road map information, Google traffic VRG module generates and sends a set of routes to the DRT module.

Data Repository and transmission module: It is a repository that keeps updated information of number of routes in graph format for requested source to destination generated by VRG module and contaminated food tracing information sent by CFT module.

3.2. Ant colony based vehicle routing model

To avoid traffic congestion situations inside and outside the city during transpiration of food stuff and reduce drivers frustration, we use the Ant Colony Based Vehicle Routing Model deployed at vehicles OBNU. This model acquires road traffic information from the Road and vehicle network and sets of routes for the requested path from the VRG module of Cloud computation.

3.2.1. Road and vehicle network

In this network, IoT based Road sensors are deployed at roadside that sense traffic flow in terms of number of vehicles, incident occurrence, road width (number of lanes) etc. and store this information with geolocation and timestamp. For efficient information transmission, road sensor nodes are grouped and form a cluster which is managed by cluster head (CH). All road sensors send their sensed information to their CH and when vehicle nodes come within the sensor range, CH injects the data information into the vehicle's OBNU. Vehicle is equipped with a vehicular sensor unit (VSU), Application Unit (AU), 802.11n interface and On-Board Navigation Unit (OBNU). Vehicular sensor units sense vehicle information like speed, mileage etc, and send this information to other vehicles that come in the sensor range which in turn broadcast messages to another vehicle. Vehicles OBNU acts as a gateway between Road-Side Network and Vehicle Network. This sensing information is then further used by Vehicle Route generator (VRG) at cloud for finding optimal route path for requested source and destination.

3.2.2. Dynamic vehicle routing with ant colony route optimization

Each route is identified by traffic density flow (td_{ij}), distance (ds_{ij}), and time. Traffic flow information regarding moving or non-moving vehicles for each route is obtained from the CH node of the road side sensor network and Google traffic. The main goal of our work is to perform smooth parking with optimal path solutions that satisfy three constraints: distance and time. In this paper we consider three parameters, traffic flow, distance, and time to find optimal solutions using ant colony algorithms. In each step, every ant k traverses from node i to node j to find an optimal intermediate solution. Thus each ant k computes probability and selects a path with maximum probability. We compute probability for ant k moves from intersection node i to node j using Eq. (6):

Input: Number of nodes (♯Nodes), set of routes Rt_{ij}^{n}, ♯Ants
Output: Best path route
  for each Ant_i in ♯Ants **do**
    for each N_i in (♯Nodes) **do**
      Calculate probability of route path route with Eq. (6)
      Select best path node using Eq. (7)
      BPR_n=selected best node across route
    Pheromone trail Update with Eq. (8)
    Best Path Route=BPR_n

Algorithm 3. Route finding algorithm with Ant colony.

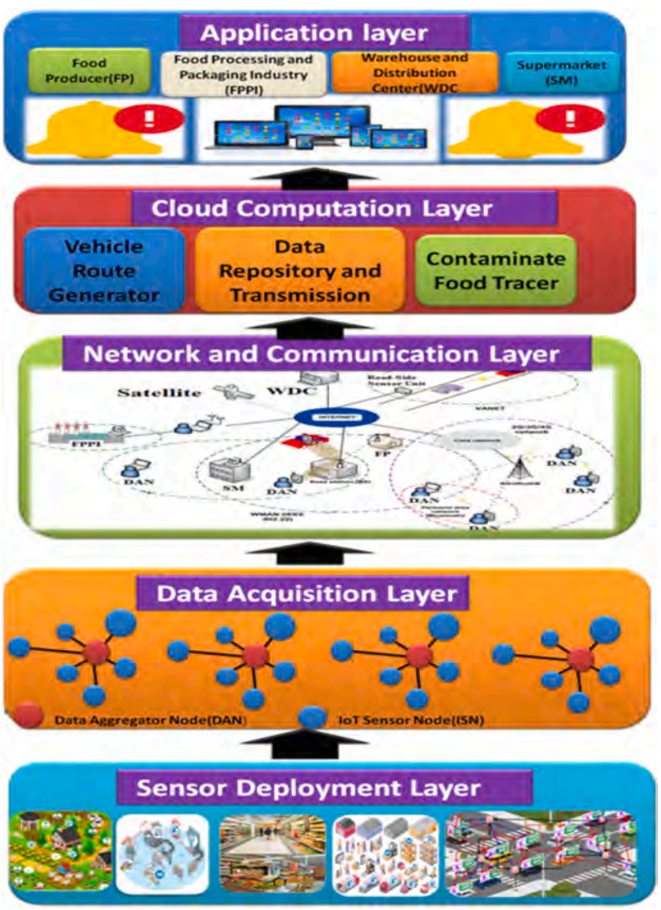

Fig. 2. Layer Architecture of proposed IoT based food supply chain.

$$Prob_{ij}^{k} = \frac{(td_{ij})^{\alpha}(ds_{ij})^{\beta}}{\sum_{senv}(td_{iu})^{\alpha}(ds_{iu})^{\beta}} \tag{6}$$

Where, α and β represent power control factor of trail intensity (td_{ij}) and distance (ds_{ij}) on the primed solution with α=0.1 and β=0.2, parameter nv represent set of un-visited intersections. Probability for the set of paths ($sP_k(i)$)originated from intersection PST_i to PST_j for each FBEE k, next we select optimal path route using Eq. (7):

$$PST_j = \begin{cases} argmax\left(Prob_{ij}^{k}\right) & nr > NR \\ Roulette\ strategy\left(Prob_{ij}^{k}\right) & Otherwise \end{cases} \tag{7}$$

Where, nr and NR are random numbers uniformly distributed from [0, 1] such that NR=0.9.

Pheromone is updated when each FBEE k completed probability construction path from intersection PST_i to PST_j and select the best optimum path. In this step, each Fast-BEE (FBEE) transformed into Block-BEE (BBEE) that update trail intensity pheromone by traversing the same path followed by FBEE k but in reverse direction using its memory and update pheromone for edge on intersection PST_i to PST_j with Eq. (8):

$$td_{ij} = (1-\omega).td_{ij} + \sum_{k}\Delta td_{ij}^{k} \tag{8}$$

Where, ω is loss (evaporation) coefficient and set to 0.1 and Δtd_{ij}^{k} additional amount of traffic on the selected route, is defined using Eq. 9:

$$\Delta td_{ij}^{k} = \sum_{m=1}^{N}\frac{Rt_{ij}^{n}}{tN_m(n)} \tag{9}$$

Where, Rt_{ij}^{n} is the se of routes generated by VRG module and $tN_m(n)$ represent time required by the vehicle k to cross ds_{ij} distance for the route Rt_{ij} with an speed s(k) based on the number of stationary cars over the route and is defined using Eq. (10):

$$tN_m(n) = \frac{ds_{ij}}{s(k)} \tag{10}$$

The ant colony continues this cycle until reaching its final destination or terminated based on conditions met. Finally suggest selecting the optimum path for the nearest parking station for requested source and destination. Route finding algorithm with Bee colony is shown in Algorithm 2.

3.2.3. Alert notification

If any issue during the entire FSC regarding safety measurement of food then alert message is transmitted to each FSC stakeholder or business logistic. Each FSC stakeholder (FP, FPPI, WDC) can access the message via mobile application using Smartphone, table, laptop etc.

Layer Architecture of Proposed Work is shown in Fig. 2 We proposed a five layer architecture consisting of Sensor deployment layer, data acquisition layer, Network and communication layer, Cloud Computation layer and Application layer.

Sensor deployment layer: At each FSC stage we deployed various sensors for measuring and monitoring food quality, safety, and freshness.

Data acquisition layer: All the sensor information is gathered by a data aggregator node (DAN) modeled with a Raspberry Pi controller that collects, aggregates, stores and transmits the sensing information to the network and communication layer.

Network and communication layer: This layer represents communication and network technologies that allow various stakeholders to communicate with each other efficiently within the supply chain network and access the information within the network. We create three tier network architecture, the first tier of network consists of IoT sensors and devices including agriculture assisted IoT based WSN nodes, RFID tags, barcodes, QR codes, user interface terminal etc. Second tier of networks represent backbone systems that consist of web servers, database systems, and terminal devices connected with distributed

Table 1
Test bed Configuration for two different scenarios.

Nomenclature	Scenario 1	Scenario 2
Number of locations/lots	30	600
Total number of food product within the food supply network	70,000	900,000
Transportation Route	Follows proposed DVRACRO	Follows proposed DVRACRO

computer networking devices. Third tier of the network represents the infrastructure of wireless and wired communication devices including Ethernet, Wi-Fi, satellite network, cellular network, power line etc. To achieve global connectivity, all the IoT devices, sensor communicating devices and backbone architecture are distributed throughout the whole food supply network and manage exchange of information with effective decision support systems.

Cloud computation layer: It performs the task of providing the best optimal path for vehicle routing during foodstuff transportation as well as tracking and tracing of contaminated food stuff via Algorithm 1.

Application layer: The smartphone enable mobile app is deployed at this layer that enable communicate with farmer, manufacturer, retailers, food analysts, government authority and consumer Each stakeholder gets alert message notification in case of any problem via various mobile application including my smart Agri-farm my food supply chain, dynamic tracing and tracking system and recall and reply assistant. With the proposed system for the Food supply chain, each stakeholder will be able to manage and analyze data information collected from the various IoT sensors, nanotechnology enabled RFID tags, barcodes and QR codes to determine food quality status and its shelf life. Customers will be able to check food quality, warranty period, product expiration dates, food testing reports, electronic ancestries, via barcodes and QR codes. Customers can also evaluate the product quality via online video and photos of that particular food product.

4. Result and discussion

In this section we represent the performance evaluation of our proposed system and algorithms over different testing scenarios and with existing approaches. We evaluate the performance of the proposed model with two scenarios for contamination tracing and dynamic vehicle routing during transportation. The test configuration for this scenario is shown in Table 1. In both the scenarios vehicle nodes act as transportation nodes between farmhouse to food factory and food factory to supermarkets.

4.1. Data collection

For data collection, we consider vehicles as bees that gather real time information about traffic and routes from road and vehicle network, Google traffic and vehicle route Generator (VRG) and execute the algorithm accordingly. Each ant is set at source point and starts traversing. All the information that is collected during the data acquisition model and computed at the cloud platform is then converted into data chunks and here we consider each data chunk as ants.

The result analysis is carried in two parts. First, we evaluate and assess the tracing and tracking accuracy of our proposed dynamically partitioned self-adaptive tracing and tracking (DPSTT) system against various testing scenario and then we evaluate the performance of Dynamic vehicle routing with Ant Colony Route Optimization (DVRACRO) against existing shortest path algorithm including Greedy algorithm and Random Allocation algorithm. The metric measure for vehicle routing algorithm is traveling time and execution time, based on these two metric measures we evaluate the performance of our proposed DVRACRO vehicle routing algorithm.

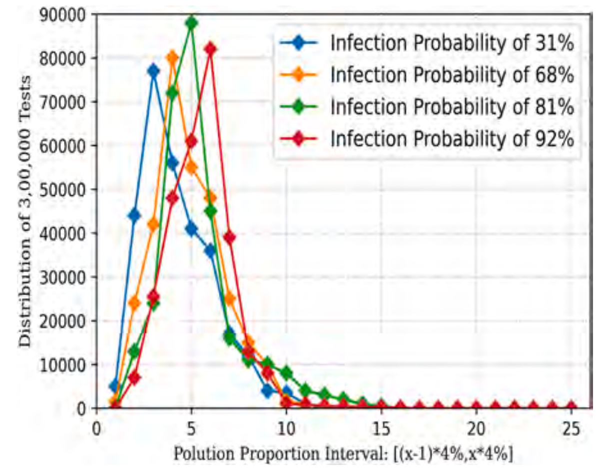

Fig. 3. Analysis of infection probability percentage.

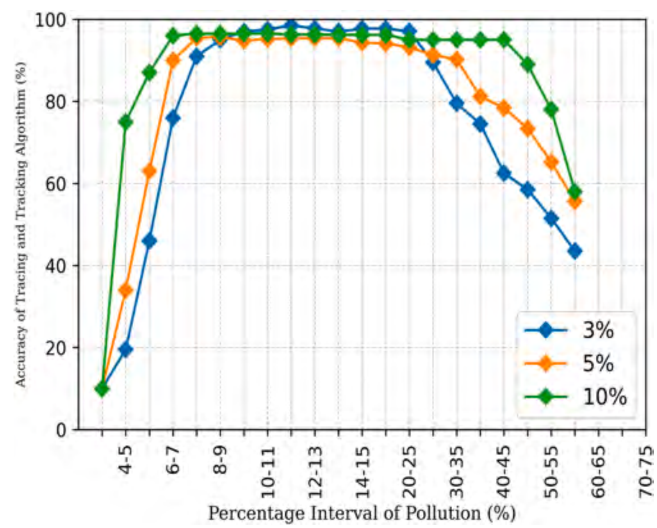

Fig. 4. Accuracy based tracing and tracking analysis.

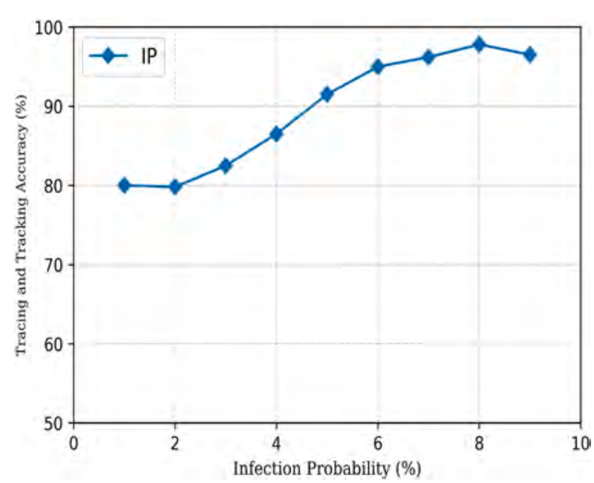

Fig. 5. Accuracy of DPSTT tracing and tracking algorithm with different infection probability percentages.

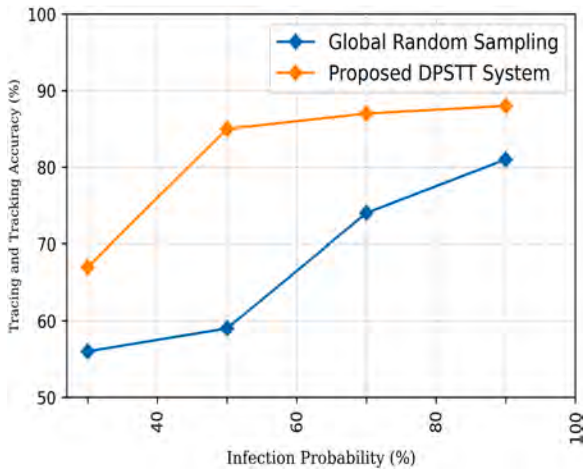

Fig. 6. Comparative analysis of proposed DPSTT with global random sampling.

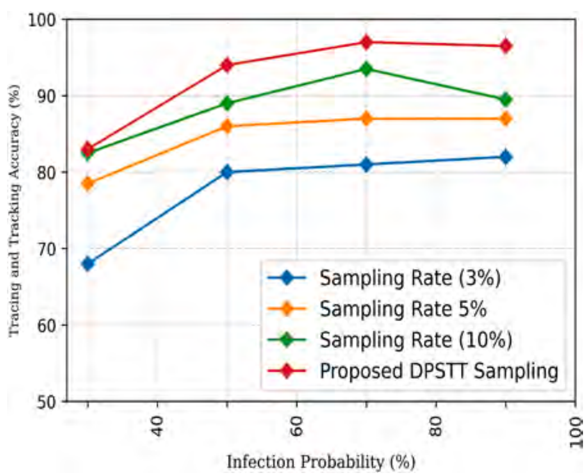

Fig. 7. Tracing tracking accuracy based on different sampling rate.

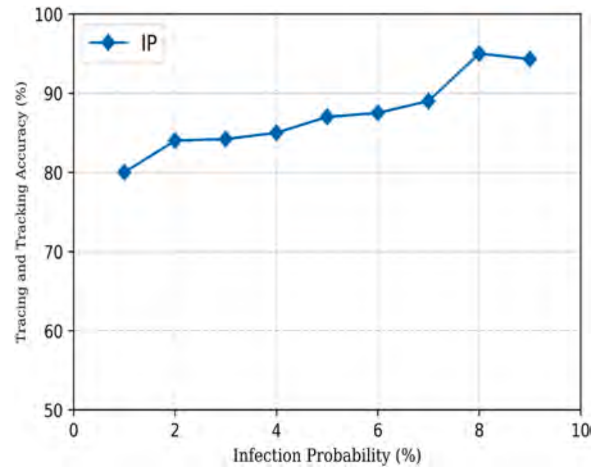

Fig. 8. Tracing tracking accuracy analysis on infection probability.

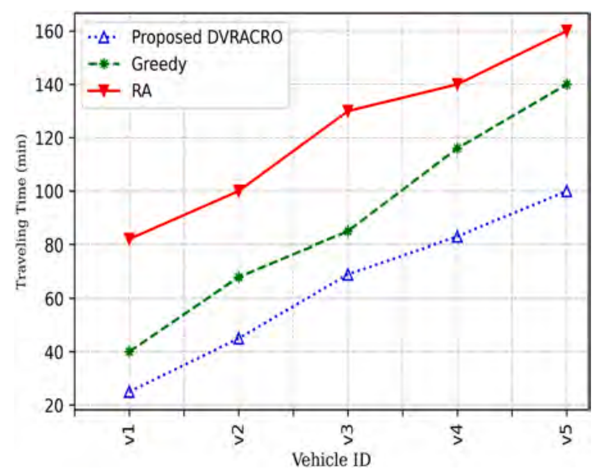

Fig. 9. Traveling time analysis of proposed vs existing approach.

4.2. Accuracy analysis of DPSTT system

4.2.1. Scenario 1

In scenario 1, we consider a total 70,000 food products within the food supply network which is sampled and partitioned into lots of 30 for every location. From which location food products will pass through will be based on the proposed vehicle routing system in order of transportation time and increase efficiency of proposed methodology. The relationship between the food product infection percentage and proposed tracing and tracking algorithm based on accuracy under diverse sampling rates is depicted in Fig. 3. For simplicity, we only consider a test bed with a sampling test rate of 10%, 5% and 3% as shown in Fig. 4.

Fig. 5 represents the accuracy of the proposed dynamically partitioned self-adaptive tracing and tracking (DPSTT) system and it shows our proposed algorithm achieve infection probability no less than 85%.

Fig. 6 represents tracing accuracy of the proposed system in comparison to the global sampling approach. For different cases of infection probabilities, the proposed DPSTT system achieves higher accuracy of 31%, 68%, 81% and 92% in comparison to the global sampling approach that has accuracy of 12%, 23%,11% and 4.5%. Moreover, Fig. 7 represents that proposed DPSTT system get high accuracy under low and average sample rate of 7.6% in comparison to fixed sampling rate of 10%, 5% and 3%.

4.3. Scenario 2

In scenario 2 we consider a large database with a total 900,000 food products within the supply chain network which is sampled and partitioned into 600 batch-lots for every place and location. In this scenario with a large database, again our proposed DPSTT system achieve accuracy more than 80% under the average sampling rate of 7.6% as shown in Fig. 8.

4.4. Comparative analysis between proposed DVRACRO and existing algorithm based on traveling time

Result analysis based on traveling time for proposed DVRACRO vehicle routing algorithm with Greedy algorithm and Random Allocation approach is shown in Fig. 9. From Fig. 9 it is observed that the proposed DVRACRO vehicle routing algorithm proposes minimum time for requested source and destination in comparison to greedy algorithm and random allocation method. Greedy algorithm picks shortest route as best route without considering traffic density flow while random allocation allocates the route to vehicle randomly irrespective of distance and traffic density flow whereas our proposed DVRACRO vehicle routing algorithm chooses best route with minimum traffic, time and distance.

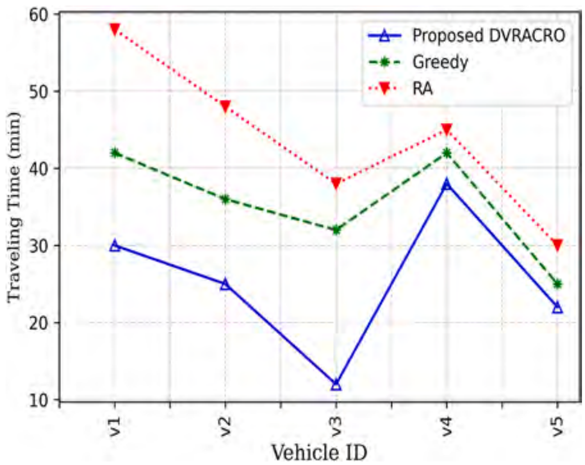

Fig. 10. Comparative analysis of proposed vs existing approach based on execution time.

4.5. Comparative analysis between proposed DVRACRO and existing algorithm based on execution time

Execution time is the time taken by the system to evaluate and find the best optimal path for a given request (nearest parking station with smooth parking at parking slot) by evaluating the time from request handling toward smooth parking at parking slot in nearest parking station taken by vehicle driver. From Fig. 10 it is evident our proposed DVRACRO vehicle routing algorithm outperform over greedy approach and random allocation strategy as our distributed approach with set of agents fully utilize parallel execution approach that search and find best optimal solution in least time by executing the work in parallel while other existing approach including random allocation and greedy approach that follow sequential execution approach which consume more CPU execution time and memory.

5. Conclusion

In this paper, we present IoT based Food Supply chain network that efficient trace and track the contaminate food product within supply chain network and also determine the source of contaminated food product. Moreover, we also present dynamic vehicle routing using Bee Colony algorithm to minimize the traveling and execution time during transportation. In the proposed work first, we proposed DPSTT system that trace and track the contaminated food product and root source using Bayesian estimation based dynamic sampling and portioning approach and later trace and track the food product DAG graph and DFS traversal scheme. From result analysis, it is indicated that our DPSTT tracing and tracking algorithm achieve tracing accuracy of 95.3% under minimum sampling rate of 7.6% in comparison to traditional global sampling approach. In addition to outperforming tracing accuracy, we demonstrate comparison analysis of proposed dynamic routing models with existing algorithms including greedy and random allocation based on comparison parameters including execution time, traveling time, and delay. The performance evaluation analysis illustrates that the proposed model suggests the best optimal path that provides minimum traveling time, minimum delay and minimum execution time. In this work, we supposed that all source information of foodstuff is compared by a central repository and these metadata sources are systematized in a uniform way. In future, this work can be extended by (1) performing cloud computation tasks at the network edge itself for more delay optimization and less energy consumption. (2) Real-world application of the provenance of the food supply chain in a community as our testing bed for megacity management.

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

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References

Allam, Z., & Newman, P. (2018). Redefining the smart city: Culture, metabolism and governance. *Smart Cities, 1*(1), 4–25.

de Amorim, W. S., Valduga, I. B., Ribeiro, J.a. M. P., Williamson, V. G., Krauser, G. E., Magtoto, M. K., de Andrade, J. B. S. O., et al. (2018). The nexus between water, energy, and food in the context of the global risks: An analysis of the interactions between food, water, and energy security. *Environmental Impact Assessment Review, 72*, 1–11.

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and supply chain management: A literature review. *International Journal of Production Research, 57* (15–16), 4719–4742.

Ben-Daya, M., Hassini, E., Bahroun, Z., & Banimfreg, B. H. (2020). The role of internet of things in food supply chain quality management: A review. *Quality Management Journal, 28*(1), 17–40.

Cardoso, S. R., Barbosa-Póvoa, A. P. F. D., & Relvas, S. (2013). Design and planning of supply chains with integration of reverse logistics activities under demand uncertainty. *European Journal of Operational Research, 226*(3), 436–451.

Chang, N.-B., Hossain, U., Valencia, A., Qiu, J., & Kapucu, N. (2020). The role of food-energy-water nexus analyses in urban growth models for urban sustainability: A review of synergistic framework. *Sustainable Cities and Society*, 102486.

Cooper, M. C., Lambert, D. M., & Pagh, J. D. (1997). Supply chain management: More than a new name for logistics. *The International Journal of Logistics Management, 8*(1), 1–14.

Djehdian, L. A., Chini, C. M., Marston, L., Konar, M., & Stillwell, A. S. (2019). Exposure of urban food–energy–water (FEW) systems to water scarcity. *Sustainable Cities and Society, 50*, 101621.

Drangert, J.-O. (2021). Urban water and food security in this century and beyond: Resource-smart cities and residents. *Ambio, 50*(3), 679–692.

Eksoz, C., Mansouri, S. A., & Bourlakis, M. (2014). Collaborative forecasting in the food supply chain: A conceptual framework. *International Journal of Production Economics, 158*, 120–135.

Esteves, V. M. C., Sousa, J. A. M. C., Silva, C. A., Povoa, A. P. B., & Gomes, M. I. (2012). Scant-design: Closed loop supply chain design using ant colony optimization. *Proceedings of the IEEE congress on evolutionary computation* (pp. 1–8). IEEE.

Filippini, R., Mazzocchi, C., & Corsi, S. (2019). The contribution of urban food policies toward food security in developing and developed countries: A network analysis approach. *Sustainable Cities and Society, 47*, 101506.

Fox, M., Mitchell, M., Dean, M., Elliott, C., & Campbell, K. (2018). The seafood supply chain from a fraudulent perspective. *Food Security, 10*(4), 939–963.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems, 29*(7), 1645–1660.

Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics, 154*, 72–80.

Jasmi, M. F. A., & Fernando, Y. (2018). Drivers of maritime green supply chain management. *Sustainable Cities and Society, 43*, 366–383.

Kelepouris, T., Pramatari, K., & Doukidis, G. (2007). RFID-enabled traceability in the food supply chain. *Industrial Management & Data Systems, 107*(2), 183–200. https://doi.org/10.1108/02635570710723804

Li, S., Da Xu, L., & Zhao, S. (2015). The internet of things: A survey. *Information Systems Frontiers, 17*(2), 243–259.

Mao, D., Wang, F., Hao, Z., & Li, H. (2018). Credit evaluation system based on blockchain for multiple stakeholders in the food supply chain. *International Journal of Environmental Research And Public Health, 15*(8), 1627.

Maye, D. (2019). Smart food city: Conceptual relations between smart city planning, urban food systems and innovation theory. *City, Culture and Society, 16*, 18–24.

Regattieri, A., Gamberi, M., & Manzini, R. (2007). Traceability of food products: General framework and experimental evidence. *Journal of Food Engineering, 81*(2), 347–356.

Sanyal, S., Kumar Singh, V., Xhafa, F., Sanyal, B., & Mukhopadhyay, S. (2021). A game theoretic framework for surplus food distribution in smart cities and beyond. *Applied Sciences, 11*(11), 5058.

Sharda, S., Singh, M., & Sharma, K. (2020). Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities. *Sustainable Cities and Society*, 102517.

Sloane, A., & Oreilly, S. (2013). The emergence of supply network ecosystems: A social network analysis perspective. *Production Planning & Control, 24*(7), 621–639.

Tian, F. (2017). A supply chain traceability system for food safety based on HACCP, blockchain & Internet of Things. *Proceedings of the international conference on service systems and service management* (pp. 1–6). IEEE.

Verdouw, C. N., Wolfert, J., Beulens, A., & Rialland, A. (2016). Virtualization of food supply chains with the Internet of Things. *Journal of Food Engineering, 176*, 128–136.

Yan, B., Hu, D., & Shi, P. (2012). A traceable platform of aquatic foods supply chain based on RFID and EPC Internet of Things. *International Journal of RF Technologies, 4* (1), 55–70.

Ying, F., & Fengquan, L. (2013). Application of Internet of Things to the monitoring system for food quality safety. *Proceedings of the fourth international conference on digital manufacturing & automation* (pp. 296–298). IEEE.