IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Exploring Last Mile Drone Logistics in Urban/Rural Areas: A Viability Study

[1]Arun Chakravarthy R, [2]Arun M, [3]Sathish R, [4]Sureshkumar C, [5]Rajasekaran S, [6]Joel Anandraj E

[1]Associate Professor, [2]Associate Professor, [3]Assistant Professor, [4]Assistant Professor, [5]Assistant Professor, [6]Assistant Professor
[1-2]Electronics and Communication Engineering, [3]Artificial Intelligence and Data Science, [4-6]Information Technology
[1-6]KGiSL Institute of Technology, Coimbatore, India

Abstract: Emergency logistics distribution is especially critical in the face of frequent public emergencies. As such, the model of coordinated delivery of vehicles and Unmanned Aerial Vehicles (UAVs) is becoming increasingly important due to the unique advantages of UAVs. However, the omission of start-up costs means the cost of UAV battery replacement and the sorting, assembly and verification of packages are not included in the total cost. Additionally, most existing models are focused on route optimization and delivery cost, which cannot accurately reflect customer demand for service satisfaction in emergencies. To address this, it is necessary to convert the unsatisfactory degree of time window into a penalty cost rather than a model constraint. Furthermore, there is a lack of analysis on the mutual waiting cost between vehicles and UAVs when one of them is performing delivery tasks. With this in mind, this paper proposes a collaborative delivery path optimization model for vehicles and UAVs to minimize the total distribution cost. This model is 20% cheaper than the vehicle-only delivery model and 25% less costly than the UAV-only delivery model. Though its delivery price is slightly higher than the vehicle-UAV collaborative delivery model, the reduction in start-up and penalty costs bring the overall cost of distribution down by 10%. This indicates that to save money and use fewer resources, the vehicle-UAV collaborative delivery model is the better option for emergency distribution. Additionally, this model which takes into account start-up, penalty and waiting costs can better express the necessity for timely UAV delivery in emergency circumstances.

***Index Terms* - Unmanned Aerial Vehicle, Unmanned Aerial System, Last mile delivery**

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) are a new form of transportation that has a wide range of applications in logistics distribution, particularly for cities with complex terrain. In order to exploit the advantages of traditional vehicle delivery, this paper proposes a joint delivery mode of UAV and vehicle, comprising of three steps. Firstly, all special nodes must be marked. Secondly, the routes of UAV and vehicle must be planned. Lastly, the total delivery route must be optimized in order to minimize the total delivery distance. Genetic algorithms and the optimization of single distribution terminals are used to solve this problem, and the joint delivery is compared with traditional vehicle delivery and independent delivery of UAV and vehicle. The results show that UAV and vehicle can collaborate to fulfill customer demands and the joint delivery can reduce the total delivery distance. Additionally, a sensitivity analysis of UAV’s maximum load, maximum flight distance, relative speed between UAV and vehicle, and road impedance coefficient is conducted. The analysis reveals that by decreasing the restrictions on UAVs, they can deliver more customers at once, enabling an efficient delivery process with vehicles.

Civil UAVs can effectively transport goods in difficult terrain, and their flexible flight routes reduce the difficulty of "last mile" delivery. As e-commerce continues to advance, companies and customers are looking for quicker and more efficient logistics. However, in cities with mountainous terrain and bad traffic, distribution is often obstructed by hills and rivers. Finding an effective way to complete the "last mile" of delivery is a pressing issue. Civil unmanned aerial vehicles (UAVs) offer a novel solution to this challenge. They are capable of transporting goods in tricky terrain, and their adaptable flight paths can reduce the difficulty of the "last mile" delivery.

At first, UAVs (Unmanned Aerial Vehicles, or Drones) were mainly utilized for operations that required coordination in the military field [1]. As of recent, civilian UAVs have seen rapid growth in development. With their convenient operation, flexible use, high operating efficiency, and relatively lower costs [2], they have been used in wider applications such as logistics distribution, surveillance cruise, emergency rescue, and medical transportation [3–7]. However, due to their limited load capacity and inability to support long-distance flights, there are many restrictions when it comes to delivering goods. Meanwhile, traditional delivery vehicles have the advantages of larger load capacity and long-distance transportation which can be combined to create a massive delivery potential. Therefore, this has become one of the most researched topics in recent years.

II. UAV INVESTIGATION

Conducting a full forensic examination of drones can be a daunting task for digital forensic investigators due to several factors. These can include the complexity of the technology, the lack of standardization, and the potential data security issues. The components of a small unmanned aerial system (sUAS) (e.g., drone, radio controller, server) can be scattered in various locations, which can make it difficult to establish a definitive connection between the hardware and its owner. Additionally, the digital containers embedded in a typical UAV aircraft require multiple forensic tools to extract all the information needed for the investigation. Similarly, direct access to the on-board camera is not always possible, as many drones provide USB connections that do not allow for forensic imaging. Consequently, forensic investigators must resort to wireless connections to perform forensic imaging remotely (over a network).

The investigation of embedded data storage containers such as flight data residing in the flight controller chip can be challenging due to access restrictions and lack of standardization. As a result, forensic investigators may need to establish a Telnet session with the UAV and use standard commands to browse system folders and configuration files. Additionally, there is no defacto standard protocol for flight controllers nor a standard format for representing flight data, and many vendors rely on proprietary solutions. Making matters more difficult, users can enhance the functionality of a drone by using software development kits (SDKs) from the manufacturer, which can further complicate the forensic analysis due to the varying types of file systems hosted on a single UAV aircraft.

Access to flight data through the on-board flight controller chip requires explicit owner permission through the remote control, however, since it is often unavailable to forensic investigators, the data is usually encrypted. This lack of remote control makes the investigation more complex. Volatile memory is used by drones, and if the battery runs out, the flight data stored within it is lost. Additionally, some sensor data may be programmed to be shared via secure servers, file sharing sites, or social networks. Not all commercial drones have flight controllers with data logging capabilities, and when the controller is not seized with the drone, it may be impossible to determine the drone's ownership based on a forensic analysis of its digital content.

The goal is to handle these tasks in a manner which is secure, efficient, and allows for an optimal forensics process. To achieve this, we use a combination of tools and technologies including cryptography, distributed ledger technology, and machine learning. Our approach enables us to securely store and access data from drones, while also providing a mechanism for verifying the integrity of the data and the identity of the drone's owner. We also identify and analyze the data from the drone's logs and other digital content, in order to provide a comprehensive picture of its operation.

This contribution addresses the challenges associated with drone forensics, by using a combination of tools and technologies such as cryptography, distributed ledger technology, and machine learning. Our approach allows for secure storage and access of data from drones, while also providing a means of verifying the integrity of the data and the identity of the owner. We also analyze data from the drone's logs and other digital content, in order to provide a comprehensive view of its operation. Furthermore, we use FTP and serial connections to access the file system in a secure, efficient, and optimal manner.

III. METHODOLOGY

This contribution is intended to address a variety of drone forensics challenges, including the intricate task of accessing the file system (which is done in our case via FTP and serial connections) as well as the assertion of drone ownership based on the extracted digital content. Furthermore, drones are composed of several components, including radio transceiver modules, CPUs, internal flash memories, flight controller chips (which may have data logging capabilities), multiple sensors (optical image sensors, inertial and velocity sensors, magnetometers, GPS sensors, etc.), compasses, batteries, collision avoidance detectors, spectrometers and spectrophotometers, wireless routers, optional cameras, removable SD cards, engines, QR codes, serial and model numbers, optional small solar panels, and payloads. Additionally, drone systems may include a battery charging system, a radio controller or smartphone with a dedicated flight navigation application, an optional Wi-Fi range extender, an optional laptop for configuration, and a server (on the ground or in the cloud) for data storage.

This paper provides the following definitions for examination: vehicles, impedance, joint delivery, independent delivery, and docking point. Vehicles refer to trucks, tricycles, and other means of transportation that can deliver goods and support UAV launch and return. Impedance refers to the non-linear coefficient, slope, and flatness of the road, along with other factors that might disrupt the uniform and smooth movement of the vehicle. Joint delivery requires the UAV to pick up the goods from the vehicle, then deliver them before returning to the vehicle. The vehicle can carry the UAV for delivery, as well as simultaneously deliver other customer points after the UAV picks up the goods. Both the vehicle and UAV collaborate to deliver all customer points based on the particular characteristics of the customer points. On the other hand, independent delivery implies that the vehicle and UAVs independently complete their own delivery tasks. Finally, a docking point can be utilized for the vehicle to park and wait for the UAV. The UAV can replace the battery, remove the goods, or launch and recover at the docking point, which might be any customer point or delivery center.

IV. PROBLEM DESCRIPTION

The vehicle and UAV collaborative delivery model is a logistics service model in which the vehicle and UAV cooperate to conduct multiple distribution tasks. This model is especially suitable for emergency distribution. The vehicle transports the UAV and the goods to be delivered from the distribution center to the customer's location according to a pre-planned route. Meanwhile, the UAV autonomously picks up the goods to be delivered from the vehicle, and flies to another customer location to deliver the goods. After completing its assigned delivery task, the UAV returns to the customer's location where the vehicle is currently, picks up the goods and replaces the battery, and continues to the next delivery task. This process is repeated until both the vehicle and the UAV have completed all the delivery tasks, and then both return to the distribution center. As there are usually constraints on the vehicle and UAV delivery process, such as UAV load, flight distance, delivery sequence, and battery life, as well as vehicle load and stopping points, the challenge is to plan the vehicle and UAV paths that minimize the total delivery cost.

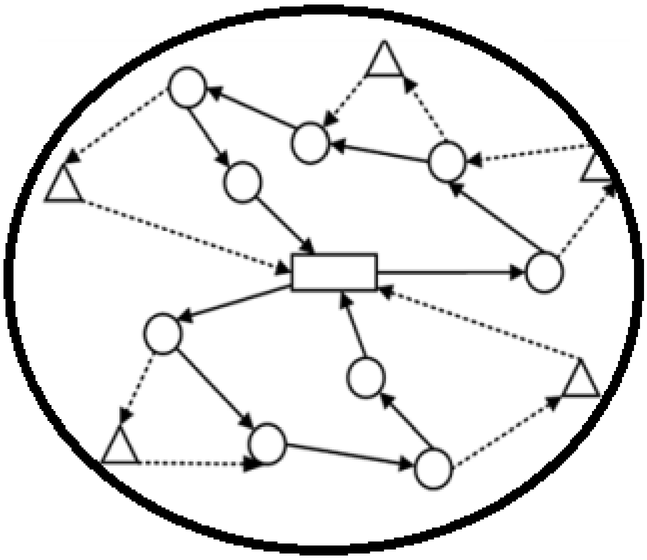

Figure 1: Schematic Diagram for Node Distribution for UAV

In the vehicle-UAV collaborative distribution model, each distribution route is a combination of the vehicle path and the UAV path. This leads to a number of distinct delivery units. The route, while the UAV is simply charging on the vehicle. A route section that is solely serviced by the vehicle and the UAV is not involved. The primary distribution unit of the UAV, consisting of the take-off point, distribution point, and landing point, which are all vehicle delivery customer points. there are a number of consecutive customer points in the UAV's basic delivery unit. The vehicle-UAV collaborative distribution is a more efficient and reliable delivery process.

In order to streamline the delivery process and simplify the customer nodes and vehicle models, the following conditions must be met: (1) customer points demand should not exceed the maximum load limit of the UAV; (2) all vehicles should have identical models and parameters, but maximum flight distance, maximum load weight and maximum endurance time should be taken into consideration; (3) no traffic jams should occur during the delivery process; (4) UAV should only serve one customer point per flight, yet after taking off, it can deliver to multiple customers; (5) each customer node should be served once without any repetition and the vehicle or UAV must return to the distribution center once the distribution tasks are completed.

IV. PHASES

Phase One: Carry out a factory reset on the drone and its controller (the Android smartphone in this case) to clear out configuration settings and erase any old data such as past flight data and video cache from NVRAM.
Phase Two: Install the AR.Freelight application on the smartphone and set up some simulated flight scenarios that include image captures and video recordings.
Phase Three: Switch off the drone and use the disk dump (dd) utility to create an image file of the entire disk. Extract any embedded digital evidence which may include flight data, EXIF data from recorded media files and ownership data etc.
Phase Four: The forensic investigation, Exiftool can be used to analyze the metadata on JPEG and MP4 files. The userbox file generated each time a flight session is established with the Parrot AR drone 2.0 is also subject to analysis, containing both configuration information such as firmware version, serial number, total flight time, and flight settings, as well as navigation data such as drone status, attitude, speed, sensor data, battery level, and GPS details.
Furthermore, artifacts and digital containers, including Linux file systems, registry settings, path flight logs, and hidden files can be examined. By aggregating and correlating the collected evidence, events or actions can be reconstructed in order to generate initial hypotheses and provide facts.
Phase Five involves testing of the hypotheses, with experiments conducted to validate or refute them. If the test results do not support the hypotheses, they must be revised and further tests performed.
In the final phase, the key findings of the forensic investigation are provided, along with the associated levels of confidence. A detailed description of the steps taken throughout the investigation is also provided, and all information related to the acquisition and analysis phases is documented.

4.1 Implementation

The original classifier for ImageNet adds one 512-dim fully-connected layer and one classification layer after the pooling layer. We train the model using stochastic gradient descent with a momentum of 0.9. The learning rate for the newly added layers is 0.01 and 0.001 for the rest of the layers. The dropout rate is set to 0.75. During the training process, images are resized to 256 × 256 pixels. We also perform basic data augmentation, including horizontal flipping and random rotation for satellite-view images. At the testing phase, we use the trained CNN to extract features from different sources. We use cosine distance to calculate the similarity between the query and candidate images in the gallery and the final retrieval result is based on the similarity ranking. For the baseline model, we choose Model-III, which fully utilizes the annotated data. Furthermore, we share the weights of Fs and Fd, as both sources of aerial views share some similar patterns.
The drone-view images are more advantageous than ground-view images when it comes to searches for satellite-view images. This is because drone-view images are taken from a similar aerial view, allowing for a more accurate comparison to satellite images. Additionally, drone-view images can avoid obstacles such as trees that can be present in ground-view images. To test this assumption, we trained a baseline model to extract visual features from three different types of data. The results showed that drone-view queries outperformed ground-view queries when searching for relevant satellite-view images. Our baseline model has achieved accuracy of 60% and an AP accuracy of 70%.

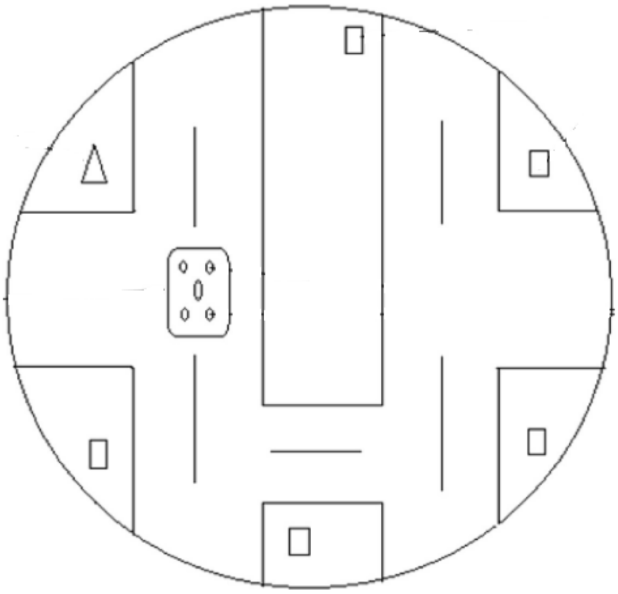

Figure 2: Representation of particular area for delivery point

The electric truck leaves from the warehouse carrying the products that need to be delivered, and the drones are on the rooftop in a charging mode. There will be one electric truck but multiple drones on the roof of the truck for a particular region (and multiple trucks in general). Electric trucks will have solar panels, and thus, trucks will act as a charging station and carry products that need to deliver. The product needs to be delivered within a minimum (5 h) to maximum (24 h) meeting consumer demand and will lead to consumer satisfaction and reduce delivery time with no CO2 emissions. Proceeding to the Company 'y' App, the consumer must then type the Region name. Accordingly, the software will indicate the warehouse name according to the Region or Pin Code. By searching in the particular warehouse product list, the consumer can place an order for any product according to the weight factor. The maximum weight a drone can carry is 25 kg, and if the product is not available, the website will show when the product will be available in a particular warehouse. The consumer will receive the message when it is available on the registered mobile number.

The UAV has the capacity of six to eight drones for delivery purposes. Through the integrated mapping system, c*ustomers* can monitor the delivery like they would with apps such as Uber or Ola. The customer will be notified 5 minutes prior to the product arriving. A card with a unique QR code will be provided to the customer and, when scanned by the drone's lidar sensors, the handler of the truck will be given access to deliver the product. For further assurance that the products are not being taken by the wrong person, fingerprint or facial recognition may be utilized. In the case of multiple deliveries in the same area, drones can deliver items depending on their capacity, and if the deliveries are within 50-100 meters of each other, the same drone can transport them in descending order.

V. CONCLUSION

Two models for the implementation of drone technology in the logistics sector were developed and modified in this article. Examples of real-world scenarios were provided to either replace existing truck delivery or develop a hybrid truck-drone delivery. It was noted that in densely populated cities, there may be overcrowded areas of infrastructure that can present challenges for drone flights. To avoid this, it is recommended to place charging towers at intervals of 2 miles, according to the big data gathered from customer demand in the area. Additionally, drones are easy to sanitize after each delivery, making them a key asset in the Indian supply chain and logistics systems in this era, as touchless delivery is of utmost importance.

5.1 Implications

This article aimed to provide practicing managers with guidance on implementing drone-delivery systems into the supply chain and logistics management of highly populated urban cities. Different demand conditions were discussed to give insight into how the two proposed systems may be implemented effectively to overcome critical challenges faced in last-mile logistics operations. The hybrid truck–drone model, with real case scenarios, suggests companies may use drones to deliver small packages in congested areas, while delivery men associated with the truck may deliver heavy parcels, reducing overall delivery time. The drone-only model offers companies the opportunity to upgrade their current logistics facilities with drone technology. There may be some economic barriers to overcome, such as the high cost of setting up separate charging or docking stations. Nevertheless, the long-term benefits include eliminating the need for trucks, achieving eco-friendly parcel delivery and reducing associated operational costs.

5.2 Limitations

In the past decade, technological advancements in the drone industry have been significant, yet there is still a great deal of potential for future research. This article does not address the plan of implementation for collaborating drones with existing logistics companies, nor does it provide computational simulations for the demonstrated real case scenarios. Additionally, it does not consider the feasibility and profitability of drone-delivery services. A survey could be conducted to determine how companies may feel about taking such a big step, which includes significant initial investments and safety considerations. Furthermore, companies may use big data from their delivery detailed data sets to project future demands and build the charging towers accordingly. Qualitative and economic analysis of drone logistics could be conducted to assess all the costs associated with drone-delivery services, including the cost of multiple drones, setting up charging stations, and forecasting costs. Lastly, the design of charging stations to accommodate numerous drones and technology for continuous delivery and quick charging should be addressed.

REFERENCES

[1] Regal Animus. 2015. Fly High 1 "UIUC" - Free Creative Commons Download.https://www.youtube.com/watch?v=jOC-WJW7GAg.

[2] Relja Arandjelovic, Petr Gronat, Akihiko Torii, Tomas Pajdla, and Josef Sivic.2016. NetVLAD: CNN architecture for weakly supervised place recognition. InProceedings of the IEEE conference on computer vision and pattern recognition. 5297–5307.

[3] Simran Brar, Ralph Rabbat, Vishal Raithatha, George Runcie, and Andrew Yu.2015. Drones for Deliveries. Sutardja Center for Entrepreneurship & Technology,University of California, Berkeley, Technical Report 8 (2015), 2015.

[4] Sudong Cai, Yulan Guo, Salman Khan, Jiwei Hu, and GongjianWen. 2019. Groundto-aerial image geo-localization with a hard exemplar reweighting triplet loss. In Proceedings of the IEEE International Conference on Computer Vision. 8391–8400.

[5] Gal Chechik, Varun Sharma, Uri Shalit, and Samy Bengio. 2010. Large scale online learning of image similarity through ranking. Journal of Machine Learning Research 11, Mar (2010), 1109–1135.

[6] Cheng Deng, Zhaojia Chen, Xianglong Liu, Xinbo Gao, and Dacheng Tao. 2018. Triplet-based deep hashing network for cross-modal retrieval. IEEE Transactions on Image Processing 27, 8 (2018), 3893–3903.

[7] Jia Deng,Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet:A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition. Ieee, 248–255.

[8] FlyLow. 2016. Oxford / Amazing flight. https://www.youtube.com/watch?v=bsrwVI_big.

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 770–778.

[10] Alexander Hermans, Lucas Beyer, and Bastian Leibe. 2017. In defense of the triplet loss for person re-identification. arXiv preprint arXiv:1703.07737 (2017).

[11] Meng-Ru Hsieh, Yen-Liang Lin, and Winston H Hsu. 2017. Drone-based object counting by spatially regularized regional proposal network. In Proceedings of the IEEE International Conference on Computer Vision. 4145–4153.

[12] Sixing Hu, Mengdan Feng, Rang MH Nguyen, and Gim Hee Lee. 2018. CVM-net: Cross-view matching network for image-based ground-to-aerial geo-localization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 7258–7267.

[13] Jonathan Krause, Benjamin Sapp, Andrew Howard, Howard Zhou, Alexander Toshev, Tom Duerig, James Philbin, and Li Fei-Fei. 2016. The unreasonable effectiveness of noisy data for fine-grained recognition. In European Conference on Computer Vision. Springer, 301–320.

[14] Peike Li, Yunchao Wei, and Yi Yang. 2020. Meta Parsing Networks: Towards Generalized Few-shot Scene Parsing with Adaptive Metric Learning. In Proceedings of the 28th ACM international conference on Multimedia.

[15] Siyi Li and Dit-Yan Yeung. 2017. Visual object tracking for unmanned aerial vehicles: A benchmark and new motion models. In Thirty-First AAAI Conference on Artificial Intelligence.

[16] Tsung-Yi Lin, Yin Cui, Serge Belongie, and James Hays. 2015. Learning deep representations for ground-to-aerial geolocalization. In Proceedings of the IEEE conference on computer vision and pattern recognition. 5007–5015.

[17] Jinxian Liu, Bingbing Ni, Yichao Yan, Peng Zhou, Shuo Cheng, and Jianguo Hu. 2018. Pose transferrable person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 4099–4108.

[18] Liu Liu and Hongdong Li. 2019. Lending Orientation to Neural Networks for Cross-view Geo-localization. CVPR (2019).

[19] Liu Liu, Hongdong Li, and Yuchao Dai. 2019. Stochastic Attraction-Repulsion Embedding for Large Scale Image Localization. In Proceedings of the IEEE International Conference on Computer Vision. 2570–2579.

[20] Hyun Oh Song, Yu Xiang, Stefanie Jegelka, and Silvio Savarese. 2016. Deep metric learning via lifted structured feature embedding. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 4004–4012.

[21] James Philbin, Ondrej Chum, Michael Isard, Josef Sivic, and Andrew Zisserman. 2007. Object retrieval with large vocabularies and fast spatial matching. In CVPR.

[22] James Philbin, Ondrej Chum, Michael Isard, Josef Sivic, and Andrew Zisserman. 2008. Lost in quantization: Improving particular object retrieval in large scale image databases. In CVPR.

[23] F. Radenović, A. Iscen, G. Tolias, Y. Avrithis, and O. Chum. 2018. Revisiting Oxford and Paris: Large-Scale Image Retrieval Benchmarking. In CVPR.

[24] Filip Radenović, Giorgos Tolias, and Ondřej Chum. 2018. Fine-tuning CNN image retrieval with no human annotation. IEEE transactions on pattern analysis and machine intelligence 41, 7 (2018), 1655–1668.

[25] Krishna Regmi and Mubarak Shah. 2019. Bridging the domain gap for groundto-aerial image matching. In Proceedings of the IEEE International Conference on Computer Vision. 470–479

[26] Arun Chakravarthy R et. al 2021. User Mobility Science with Intelligent Location Tracking Scheme for Managing Nuclear Energy, Journal of Nuclear Energy Science & Power Generation Technology. 1-6.

[27] Arun Chakravarthy R et. al 2016. Cluster Header Revolving Technique to Prolong Network Lifespan in Wireless Sensor Network. Journal of Computational and Theoretical Nanoscience, Volume 14, Number 12, December 2017, pp. 5863-5871(9).

[28] Arun Chakravarthy R, M Arun, Ms M Bhuvaneswari. 2021. Data Science: Best Practices in Digital Transformation. Tech Trends 2021: Issues and Emerging Challenges and Changes in the Student-Centric Learning and Best Innovative Practices for Quality Enhancement in Education.

[29] Arun Chakravarthy R, M Arun, Mr C Sureshkumar. 2022. Information and Communication Technology Convergence: Rethinking Higher Education in the Post-pandemic era. Education Trends in a Post-Pandemic Future in the Fields of Engineering, Science, Arts, Humanities, Commerce, Economics, Social Sciences, Law and Management-Challenges and Opportunities.