IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received April 13, 2020, accepted April 21, 2020, date of publication April 24, 2020, date of current version May 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2990190

A Novel Simulated-Annealing Based Electric Bus System Design, Simulation, and Analysis for Dehradun Smart City

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ABSTRACT Smart transportation network development with environmental issues into consideration has brought Industry 4.0 based solutions on priority. In this direction, battery-powered electric bus systems have been considered widely for ensuring flexibility, operation cost, and lesser pollutants emission. Industry 4.0 provides automation through a cyber-physical system (CPS), the interconnection of bus system entities with industrial internet-of-things (IIoT), remote information availability through cloud computing and scientific disciplines (human-computer interaction, artificial intelligence, machine learning etc.) integration. In this work, a discrete event-based simulation-optimization approach is integrated that take care of bus energy consumption according to real-time city's passenger needs and on-road friction levels. The proposed simulation optimization methodology utilizes multi-objective with dependent and independent variables for optimizing the overall system performance. In simulation optimization, objective functions are designed to tackle battery consumption, Internet-of-Thing (IoT) network performance, cloud operations efficiency and smart scientific discipline integration. Simulation parameters are based on a real-time bus system which is further analyzed, filtered and adapted as per the needs of the system. In another analysis, supercharger's capacities are varied to evaluate the performance of the proposed system and identify the low cost and efficient smart transportation system. Simulation results show different scenarios for variations in the number of buses, charging stations, bus-depots, mobile charging facilities, and bus-schedules. Simulation results show that the average passenger's waiting time in the waiting is (after ticket booking) varies between 0.2 minutes to 0.7 minutes in real-time traffic conditions. In similar traffic conditions, total passenger's time in system (ticket booking to travel) varies between 41.6 minutes (for 24 hours) to 45.5 minutes (for 1 year). In the simulation, priorities are given to those dependent and independent variables which save the battery consumption and elongate the utilization of buses. Lastly, it is also observed that the proposed system is suitable for resource-constraint devices because Gate Equivalent (GE) calculation shows that the proposed system can be implemented between 1986 GEs (communicational cost without confidentiality and authentication) and 7939 GEs (computational cost with HMAC for authentication in data storage). This ensures varies security primitivs such as confidentiality, availability and authentication.

INDEX TERMS Electric vehicles, gate-equivalents, smart city, simulation-optimization, security primitives.

I. INTRODUCTION

Electric energy-based smart transportation system is the need for a new generation smart city's infrastructure. Electric energy has various advantages over fossil fuel energies. Fossil fuels emit nitrogen dioxide, carbon monoxide and sulfur dioxide which can cause catastrophic injury, respiratory tract infections, pulmonary diseases, cardiopulmonary adversaries, etc. Electric energy systems are renewable, environment-friendly, and provide clean energy solutions.

The associate editor coordinating the review of this manuscript and approving it for publication was Eklas Hossain.

Presently, two types (off-board and on-board) plug-in electric buses are popularly adapted in smart city infrastructure. However, a well-planned bus route, their schedules, and on-road charging station based infrastructure do not meet real-time requirements. For example, heavy traffic, change in the bus route to high altitude routes, passenger needs, long-distance travel, etc. consume more electric energy as compared to its normal operations. Thus, advanced infrastructure is required to meet the demands of a clean energy-based smart transportation system that incorporates real-time requirements. Here, Industry 4.0 standard is helpful in-terms of automation and data exchange using cyber-physical systems (CPS), industrial internet-of-things (IIoT), cloud computing, cognitive sciences, and artificial intelligence. Additionally, Fuel cells, lithium batteries, and supercapacitors integrated power system provides much higher peak current and faster reactions to electric buses [1], [2]–[5].

Electric energy-based energy management systems for electric buses are typically classified as rule-based or simulation optimization [2]–[5]. The aim of both of these approaches is to maximize the energy transfer efficiency from the primary electric source to the buses while elongating the battery lifetime. Rule-based energy management systems are either deterministic or adopt fuzzy logic control (FLC) [2]. Although a fuzzy logic based energy management system eliminates the deterministic's binary logic strategies and applies membership functions but both of these strategies work for specific application scenarios and are not suitable for dynamic conditions. In comparison to rule-based approaches, simulation optimization approaches apply active optimization functions that can easily adapt to even highly dynamic conditions within stipulated periods based on input, output, and history of variables passed. Further, the major challenges to electric buses based smart transportation system in smart city network are as follows [6], [7]:

- Electric buses based public transportation system requires dedicated and scheduled charging points with least error feasibility and opportunity charging indication system. In an opportunity charging indication system, buses can take advantage of those charging points that are free and on their travel routes. Buses can get these free charging points if they reach any charging station before time. Thus, the bus schedule should be prepared in a way that opportunity charging is possible or incorporated with dedicated infrastructure.
- Deployment of various charging methods, their locations, and schedule is important for the smooth execution of the electric bus transportation process flow.
- As compared to other fuel and charging systems, electric battery based infrastructure demands huge investment. Thus, bus routes and charging stations should be planned such that there should be maximum charging point sharing and minimum infrastructure deployment costs. Besides, the city's major routes and passengers traveling area must be covered. Possibly, important and dedicated routes should be covered in the initial deployment phase followed by other priority routes according to the system's lifecycle costs calculations.
- Integration of Industry 4.0 standards to meet the real, and known or un-known challenges are required. For example, the performance of internet-of-things (IoT) and cloud computing infrastructure provides the accurate route, charging point and bus's battery state at any location from any remote state. Thus, IoT network's QoS parameters are important to evaluate in order to measure and improve the system's efficiency.
- The electric bus system's exception conditions should be taken into consideration. For example, how the buses will operate if IoT network and/or cloud computing infrastructure malfunctions.

Dehradun is the capital city of Uttrakhand, India and has a population of approximately 0.6 million. Additionally, approximately 6-million pilgrims/tourists either pass through or visit Dehradun for 'Char Dham' shrines (Badrinath, Kedarnath, Gangotri, and Yamunotri), 'Hemkund Sahib' or other tourist places. The city lies at foothills of the Himalayas and Doon Valley, and have various other challenges such as narrow roads, high road-elevations, local transportation mainly dependent upon fossil fuel-based buses, rainy/stormy weather conditions etc. These challenges increase the complexities of electrified bus operations and decision making processes related to these operations. The government of India has taken many initiatives to promote and transfer the fossil fuel-based buses with electric buses in smart cities [8]. According to these initiatives, the government is starting a pilot project with 30 electric buses. Out of 30, 22 buses will cover major passenger-loaded routes (with a frequency of 15 minutes) and 8 buses from city to airport (with a frequency of 30 minutes) [8]. In the pilot project, initiatives for building required infrastructure including workshop, charging stations (both off-board and on-board), optical fiber infrastructure, server rooms etc. are proposed as well. The proposal to integrate electric buses and upgrade existing infrastructure is required because of following reasons [8]: (i) existing public transport system is unable to fulfill the requirements of city, (ii) existing bus system are unable to cover the whole city areas and routes, (iii) passenger's needs are to have bus services in at least 70% of roads infrastructure. Presently, it is lesser than 20%, (iv) existing bus system is not viable, convenient and reliable for passengers because of old buses model, operations over uncertain traffic conditions, long traveling time, lesser bus stoppages, etc., (v) use of non-air-conditioned and fossil fuel-based buses that increases pollution levels and (vi) cost inefficiency. After analyzing various challenges to electric buses based smart transportation system in real-life examples, this work has considered the following objectives for-proposing electrified bus model for Dehradun smart city:

- To integrate the simulation-optimization approach for battery-health monitoring, IoT network operations and bus's on-road real-time travel needs, and perform a comparative analysis with ideal conditions. In order to consider battery durability and deliberate power regulation, the error measurement model with optimization is integrated. This error measurement model will take care of all possible errors (forward, backward or origin).

• To design an electrified bus system that caters to the needs of upgraded bus models, bus routes, coverage of maximum city area and routes, passenger's requirements, bus's charts etc. Here, a paper-based model is simulated with optimization methods and advanced infrastructure requirements. Simulation and objective function parameters are opted as per real-time and future requirements.

• To test and validate the proposed system and strategies such that normal and exception conditions ensure functioning in any certain or uncertain conditions.

• To design, operate and integrate the proposed strategies, discrete event-based modeling and process flow software analysis is necessary. This analysis will determine the functionalities of overall and sub-system operations and evaluate various operational concerns including battery capacities and their operations, charging facilities and their operations, IoT network performance, data storage facilities etc.

The proposed work will improve the quality of life by improving the air-quality (no pollution, fossil-fuels etc.), environment-friendly solutions, fewer carbon footprints, incorporating smart transportation system, convenient, cheaper and timely availability of buses, pre-planning would be much easier, encourage international tourism, promote businesses (especially education, IT and hospital services) in the city etc. Additionally, the proposed system is capable to meet the exponential, present and future transportation requirements of people bus public transportation requirements. It would be much easier, transparent and convenient to monitor the whole system (including public activities) in real-time. This work is using a simulated-annealing method for solving bound-constrained optimization problems associated with networks. Here, the simulated-annealing approach is used to analyze the system performances (like energy consumption) and systematically vary the direct or indirect system parameters to meet the objective functions. The proposed simulated annealing and optimization is applied to reduce the errors and make an energy-efficient smart transportation system. A detailed smart bus transportation plan is designed, simulated and tested for Dehradun city. The detailed plan contains bus information, their routes, energy consumption in multiple systems, battery conditions, city's passenger traveling needs etc. The proposed approach is lightweight in terms of communicational and computational costs. Thus, it is efficient in response. A comparative analysis with other simulated approaches is drawn as well for analyzing the efficiency of the proposed simulated model. In result, it is observed that the proposed simulation-optimization approach reduces the error rates to a minimum of -0.04% (for average passenger time in system (minutes) with 0.5 to 0.75 million vehicles on road daily) and a maximum of 0.06% (for average charger waiting time and average queue waiting time in system). Further, the proposed approach can reduce the hardware requirements to less than 4500 GEs for security primitives and protocols.

The paper is organized as: Section 2 shows the literature survey regarding over-optimization approaches used in real-time and simulation-based electric bus systems, and other electric-based vehicle transportation networks. Section 3 presents the problem statement of the existing bus transportation system in Dehradun city that should be considered for replacement from diesel/petrol powered buses with environment safe electric buses. This section explains the proposed electric bus system design and process flow as well. The detailed proposed Industry 4.0 standard integrated simulation-optimization approach is presented in section 4. Section 5 presents the simulation and analysis of the proposed model where the proposed simulation model is mapped to a real-time scenario, executed and analyzed. Finally, the conclusion is drawn in section 6.

II. LITERATURE SURVEY

Sebastianiet. al. [1] presented a discrete event simulation approach for measuring, analyzing, evaluation and improving battery consumption in the electric bus system. In this approach, a bi-objective genetic algorithm based simulation-optimization approach is applied to the public transportation scenario through various parameters. For example, passengers in on-road buses may need a monitoring system to have their current location, distance from other destinations, bus connectivity to other destinations, travel time etc. Similarly, if a bus is unable to provide travel time to other destinations then the speed of the bus (if provided) can give this estimation. In overcrowded buses, an announcement based system providing distances to cover for subsequent stations are found to be a beneficial system. A supercharger is assumed to be taken-up for fast charging and avoiding delays. Thus, a supercharger is defined as a charging system for an electric bus with a very high charge rate (more than 300 kWh in the present time). In a simulation, multiple arrangements have been made for multiple stations, their deployment, and locations, bus-stops and delays in on-road bus schedules.

Lajunen [20] proposed overnight charging, end-station charging and opportunity charging based simulation tools to analyze lifecycle costs and replacement of fossil fuel-based buses with electric buses. This study has taken care of multiple simulation parameters into consideration to accommodate the dynamic operational nature of the electric bus system for the smart transportation network. Here, it is realized that the charging method, charging power limit and charging time are important battery charging parameters that need to be considered while designing electric buses based public transportation system. Similarly, speed profile and the number of buses stop in route selection, buses schedules, dwell time and passenger load in operation timetable, technical specifications and battery configuration in a bus configuration, and auxiliary power and battery depth of discharge in the miscellaneous category should be given major concentration in system's operational process. The electric buses based public transportation systems' overall performance is measured using various life-cycle parameters such as bus service time, their yearly operational feasibility and capabilities, battery life cycle, battery calendar lifetime and costs involved in the deployment of different technical and operational components.

Hu *et al.* [9] explored the advantages of the Hybrid Energy Storage System (HESS) and energy management using a fuel cell-based hybrid electric bus system. This works contributed in electric bus system operations through convex programming. Firstly, this programming optimizes the HESS dimensions which include lithium-ion battery and the supercapacitor stack sizes. In the proposed hybrid bus system, convex programming is found to be helpful in power allocation between HESS and fuel cell-based battery systems. These process flows are extended with a simulation optimization problem for concrete measurements of impacts of the battery replacement strategy over the two types of systems. Further, simulation optimization experimentation is extended for comparative analysis of HESS and battery-only energy storage systems. Finally, simulation optimization results measuring battery-health are contrasted with ideal scenarios. Although this compare and contrast measurements assume ideal conditions but battery deliberate power regulations are assumed to be within acceptable limits.

Kivekäset *et al.* [10] applied the simulation optimization process over stochastic driving cycles of a battery-operated electric bus. This study aims to analyze the energy consumption and improve the performance of electric bus operations in a city by considering the uncertainties over the routes. In experimental analysis, the proposed simulation-optimization approach is applied for analyzing the impact of driving cycle design and variations in the number of passengers travel over the bus's energy consumption. Results are analyzed for 10,000 synthetic cycles to validate the proposed simulation model. It is observed that the proposed approach is useful for smart public transportation system planning for a smart city because it provides a tool for them to plan bus routes, their operations and cost-effectively monitor manufacturing processes. The simulation-optimization approach is helpful in bus power train dimensions. Results show that reliable energy consumption could be acquired with 2000 simulated synthetic cycles only. An examination of 2000 to 10,000 synthetic cycles is necessary for experimentation. Further, the amount of energy consumption is found to be relevant for considering best, average and worst-case scenarios for system design. These scenarios are also helpful for achieving the desired percentage of runs and deployment of charging points.

Wang *et al.* [11] analyzed the coaxial series dual-motor coupled propulsion system for battery operated electric bus using dynamic programming. In this work, dynamic programming is integrated with single and dual-mode strategies. Simulation optimization in these strategies applies an objective function to obtain the desired power management strategy with a control unit and dynamic programming. The objective function is measured through an evaluation function that measures energy consumption and optimizes the operations of electric motors which in-turns improve the overall system efficiency. In order to validate the proposed approach, bench and vehicle tests are performed. It is observed that the multi-motor power train system is highly effective for electrified buses. The proposed benchmark is validated through a real vehicle experimental setup and results are compared.

Teoh *et al.* [12] realized the importance of green mobility to overcome the air pollution generated through fossil fuel-based public transportation systems. A simulation-optimization based approach is tried to improve the energy-consumption in buses and make them efficient. Here, energy-consumption is optimized by minimizing the auxiliary functions. The work examined the possibilities to operate an environment-friendly electric bus system as a replacement for fossil fuel-based buses. Overall, the proposed system is found to be highly profitable for bus operators and satisfy passengers with smooth and healthy travels. Further, the proposed system has a provision to carry more passengers per bus with lesser energy consumption over dedicated routes.

Nayyar *et al.* [13]–[15] proposed various smart technology solutions for industrial applications, underwater things, and buildings. These approaches have applied optimization at a different level to improve system efficiencies. All of these systems are either partially or fully integrated with industry 4.0 processes. These processes recommended system building using different networking options such as IoT, IIoT, cloud, fog and edge computing. Among all these networks, service optimization is required to have better QoS, response time, real-time operations. Further, security solutions through cyber awareness in industry 4.0 networks are discussed for smart city networks [16] and among security solutions, data collection, analysis, sharing, and evaluation are important activities [17]. Here, active and passive security solutions are proposed for smart solutions. These approaches are found to be applicable and fruitful for different applications in different scenarios. These security solutions include malware detection [18], [19], static and dynamic malware detection processes, cybercrimes [17] etc.

Puri *et al.* [23] have proposed a smart solution for agriculture and its monitoring through drones. This is an electronic solution for improving agriculture growth and precision. There is a need to integrate security solutions such as fast authentication [18], [24] to have high accuracy and precision results. An industry 4.0 based system requires security aspects into consideration while optimizing the results.

Alazab *et al.* [25] proposed an optimization of electrospinning polyethylene from water prepared from dichloromethane and acetic acid. These processes are important for electric bus batteries and their result optimizations. In [25], these approaches are applied over nanoscale fibers. However, the proposed approach with the electrospinning concept can be used for high voltage power supply capable of delivering 30kV. Here, different acid experimentations are performed to have a greater result level in the complete process.

Table 1 shows the other optimization approaches applied over the electric bus system so far with their strength

TABLE 1. Literature survey of optimization techniques in the electric bus system.

Author/s	Optimization Method	Application of Optimization Method in Electric Bus System	Strengths	Weaknesses
Sebastiani et al. [1]	Genetic Algorithm based Simulation Optimization	• Allocating charging stations. • Battery Charging. • Avoiding Bus-delays.	• Genetic operations and updates are found to be useful in avoiding delays. • Real-time scenarios are taken into consideration for simulation. • Performance analysis shows variations in charging stations, bus routes, energy consumption, and bus-stops. This analysis shows that a large number of stations can take advantage of the operations as the proposed system is less sensitive to full battery charge variations.	• The mobile battery delivery system is not feasible because batteries are very heavy (1411 kg). • Integration of IoT and Cloud platforms can make the proposed system suitable for smart cities.
Kwan et al. [2]	Non-dominated Sorting Genetic Algorithm (MSGA)	• Minimize fuel cell's fuel consumption, battery requirements and supercapacitor's size. • Find ways to avoid deterioration of battery degradation rate.	• Fuel cell power system based fuel cell electric bus operating system is designed. • Simulation optimization is used to optimize the capacitances of superchargers and the fast charging of electric bus batteries and minimize the fuel consumption and supercharger sizes. • Superchargers' size is important to consider because incorrect hardware component's combinations and sizes can result in instability or failure of the complete system. • It is observed that both software and hardware optimization is necessary. Individual optimization cannot result in system efficiency.	• This work has designed a model for fast-charging electric buses suitable for highways. • It is expected that the proposed model will output to a much higher average and peak load demands. Further, it is assumed that the proposed design will automatically be suited for slower urban environments as well. However, the model does not incorporate special geographical, environment and uncertain conditions.
Lajunen [20]	Genetic algorithm-based bi-objective simulation optimization	• To evaluate the electric bus operation under different working conditions. • To simulate bus's working conditions over different operations, charging types and on-road routes. • To identify the optimal charging type by varying the operating routes and chargers.	• Dedicated charging infrastructure and specific bus configurations are realized for the smart public transportation system. • The importance of different types of charging points (overnight, opportunity and end-station) are given importance. • The choice of charging method can vary with the type of route, traffic conditions, number of passengers etc. • Cost analysis is performed for various operations of a system's life cycle. For example, maintenance cost, charging cost, infrastructure cost, operational cost etc.	• Real-time battery requirements need to be considered as uncertain conditions can vary. Thus, the proposed model is suitable for a specific city only. It cannot be generalized for all smart public transportation networks in smart cities. • The integration of IoT network and cloud computing could enhance the proposed model with real-time traffic conditions and requirements of buses over roads. • The impact of overloading and uncertain conditions over the battery life cycle could be integrated.
Hu et al. [9]	Convex programming integrated simulation optimization	• To quantitatively examine the impact of the battery replacement approach in the proposed system that further measure the HESS size and investment in a bus. • To perform a quantitative comparative analysis of bus economy deviation with battery types.	• It is observed that the use of a large battery system with the HESS guarantee is relatively more cost-effective as compared to the battery replacement system. • State-of-Health (SoH) model is integrated with a convex programming framework and it is observed that the desired HESS dimension and power management can be achieved for battery age optimizing parameter. • It is observed that convex programming is beneficial for optimization and achieves the desired optimal HESS size and power management for the hybrid bus in a few minutes.	• In the proposed fuel cell-based hybrid electric bus system, the proposed work does not show the implementation over the real-life scenario. Thus, performance over single bus experimentation is fruitful but may not be useful for some application scenarios. • This work does not classify the dimensions that can be avoided when an optimizing approach is applied over the electrified bus powertrain. This experimentation can be extended with pre-defined simulation optimization objective functions to measure the performance of multiple dimensional parameters for the electrified bus system. This extension and corresponding outputs can validate the claims.
Li et al. [21]	Enhanced genetic algorithm is applied with simulation	• To optimize the driving cycles of an electric bus while collecting the real-time bus routes and other details.	• This approach has applied a rule-based strategy to attain the goals with a maximum of the double-parameter gear shift. Here, tradeoffs between different parameters are analyzed. • The optimization objectives are taken at multiple levels. Among initial levels, low	• The approach is applied over a hybrid battery (fossil-fuel and electric charge) system. However, the present approaches and applications require/suggest a complete electric battery system.

and weakness analysis. Various other studies are performed [26]–[28] to optimize the electric vehicle designs, battery parameters, vehicle performances, charging capacity etc. Most of these studies are over small size electric vehicles.

TABLE 1. *(Continued.)* **Literature survey of optimization techniques in the electric bus system.**

	annealing process for optimizing the bus driving cycle and driving schedule	• To optimize the availability of buses on-time to passengers with modifications in driving schedules especially in urban areas.	component costs, high dynamic performance, and high energy economy are taken as powertrain and control strategy components. • In optimization evaluations, passenger mass-distance, road slopes, bus speed, route map are considered. Results show that the proposed approach is efficient and close to real-conditions.	• The proposed approach mainly concentrates on improving the driving cycles, bus usages, covering the maximum uraban areas. However, the present system demands an electric bus system with industry 4.0 trends having optimized performances.
Wang et al. [22]	Simulation-annealing based driving cycle optimization in hybrid batteries for electric vehicle	• To optimize the driving cycles and battery capacity with supercapacitors. • To accommodate and optimize the maximum peak demands and energy absorption in the complete driving cycles of an electric vehicle.	• To design a hybrid battery system with electric circuits having rule-based current optimization and increasing the electric vehicle driving capacity. • Three driving modes (high normal and low) are considered in driving cycle testing. • In optimization, battery results in terms of open-circuit-voltage and battery resistance are evaluated for analysis. • In simulation analysis, result based simulation model, small supercapacitor design and testing optimizing results in multiple scenarios, battery size into consideration, fluctuating voltage control etc. are taken in the study.	• The proposed system lacks a complete environment-friendly solution to cities/countries having high pollution levels. • The integration of the proposed approach with industry 4.0 processes based bus transportation system is necessary to be considered to meet the futuristic requirements. • The proposed work integration with any electric vehicle design and its performance analysis is necessary to compare its working with real-time conditions.

However, electric buses or trucks are considered among heavy vehicles thus the requirements are different. These vehicles require high rate charges and long duration based electric storage capacities. Thus, the design requirements are completely different.

In literature, various studies have been performed to integrate simulation optimization with electrified bus systems [29]–[33]. However, there are many shortfalls in existing work. For example (i) the environmental protection issues arise from fossil fuel-based public transportation systems should be taken-up diligently, (ii) there is a strong need to accelerate the process of fossil-fuel-based bus system replacement with advanced infrastructure such as Industry 4 integrated electrified public transportation systems especially in the world's top polluted cities (presently, the top 22 out of 30 are in India [34]), (iii) there is need to apply simulation-optimization approach over various sub-systems including bus charging infrastructure, bus's routes, passenger's demands, special-route operations, battery capacities, and sizes etc., (iv) simulation optimization in hybrid (software and hardware) model should take network issues on priority because network operations only indicate on-road and off-road situations, and (v) in hybrid simulation-optimization approach with Industry 4 standards, on-road network issues involve traffic conditions, passengers demands, uncertainties, natural disasters etc. These issues vary over geographical locations. Thus, a base model suitable for every type of uncertainty is possible with simulation optimization and advanced infrastructure.

III. PROBLEM STATEMENT AND SYSTEM DESIGN

An energy-efficient, environment-friendly (emission-free) and fast charging electric bus system is the need of smart transportation systems for any smart city. In various studies [35]–[41], it has been observed that any form of the electric bus system (hybrid-battery or fully battery-electric) is useful in improving the life-cycle of the electric bus as well as the city's air quality. Dehradun is one of the hill cities declared to be the smart city by the Government of India [42]. It has around 363 Km of the road network and 389 buses are serving the passengers in the public transport system [43]. Although, the permits to diesel shared vehicles have been stopped in early 2012 and various initiatives have been taken to widen those junctions where there are ether frequent traffic issues or jams, but there is no alternative arrangement made on-ground. Thus, most of the public transportation systems are based on fossil fuels that are not environmentally friendly. In this work, a simulation model has been designed and used as the research method in an electric bus system for Dehradun city because it enables a fast evaluation of the proposed model under different scenarios. The outputs of the proposed model are utilized to measure the performance of the system by varying the passenger's load, bus profiles, bus routes, and timings. The performance measurements are incorporated into an iterative system's refinement approach to study impacts. Detailed system design and process flows are explained as follows:

A. ELECTRIC BUS SYSTEM DESIGN AND PROCESS FLOW

Figure 1 shows the proposed electric bus system design. Various sub-systems of the proposed system are explained as follows:

1) SMART BUS SYSTEM AUTOMATION

This sub-system automates the functioning of Bus public transportation system through industry 4.0 trends such as IIoT, IoT, IoT Cloud Computing and cognitive computing modules. Industry 4.0 trends are the smart ways of integration IoT, IIoT and Cloud IoT modules under proper statistical, administrative and supervisory controls. Various modules of this sub-system are explained as follows:

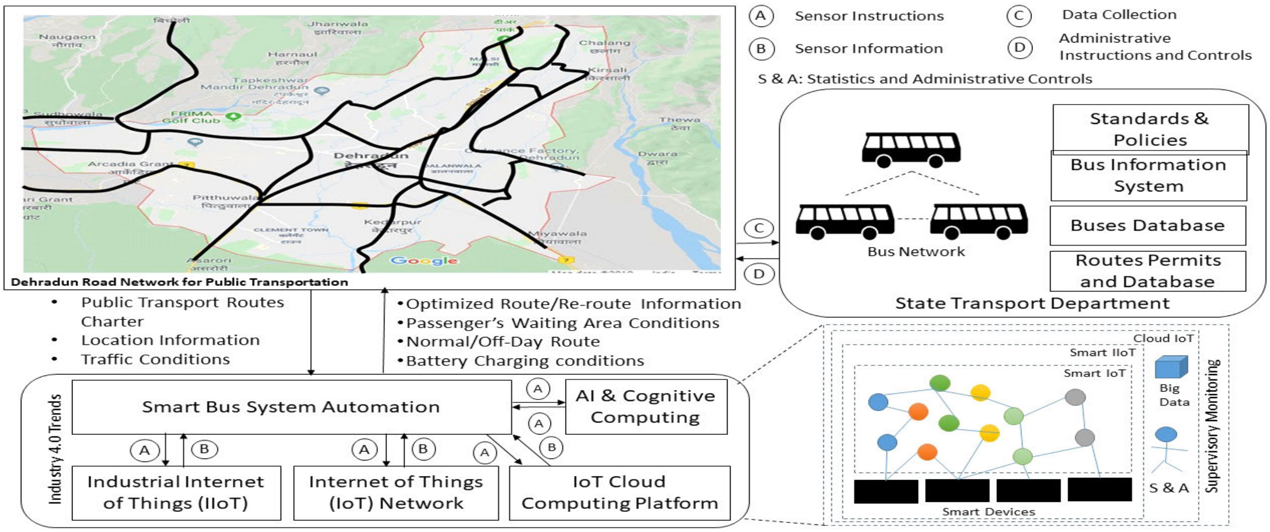

FIGURE 1. Proposed electric bus system design.

- *Industrial Internet of Things (IIoT):* In the proposed system, this module interconnects all sensors, devices (like batteries) and computer systems for data collection, storage, and analysis. IIoT provides a distributed environment for administration, monitoring and control.
- *Internet of Things (IoT):* The proposed system considers IIoT different from IoT in terms of handling sophisticated and critical devices, taking control over sensitive and precise sensors to avoid failures and high-risk applications. On the other hand, IoT network is mainly used when passenger interactively interacts with the system.
- *IoT Cloud Computing Platform:* IoT cloud computing platform uses a steepest-descent optimization approach to refine and optimize the administrative and statistical controls. Further, this process implements a high-degree of automation.
- *AI & Cognitive Computing:* In the proposed system, this concept smartly handles the large volume of data influx and data analytics complexity. All the system assets (including buses, servers, display units, batteries, sensors etc.) take advantage of cognitive computing in providing error-free intelligent systems. The cognitive computing smartly combines data received from different stakeholders (individual passengers, servers, IoT network, IIoT network etc.).

2) STATE TRANSPORT DEPARTMENT

This sub-system seeks permission from the government and follows the standards and policies (for vehicles, driving etc.) required to run public transport services. Besides, this department database stores bus details, routes associated with buses in the bus information system and route permits and databases.

Figure 2 shows the passenger bus interactive process flow diagram. In this flow, a passenger walk-up to the bus waiting

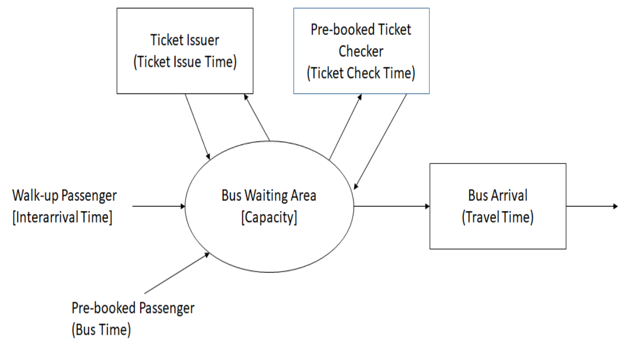

FIGURE 2. Passenger - bus interactive process flow diagram.

area and wait for a bus. Each bus has a fixed capacity and a person employed for ticket issue and checking. In every bus, preference is given to pre-booked passengers over passengers without a ticket during boarding. After the bus starts its journey, a ticket checker cross-checks all passenger tickets and issue a ticket to those passengers who have not purchased it. Figure 3 shows this flow in-detail. A passenger arrives at a bus stop and waits in the passenger waiting area. A bus timing display is available in the waiting space for checking bus availability, its route, its number and arrival time. Once a bus arrives at its stop, the ticket checker makes a call to all pre-booked passengers to board the bus first and thereafter, passengers without tickets are called as per seat availability. The bus stops at its bus-stop for a fixed duration and starts its journey. After the ticket checker asks pre-booked ticket passengers to verify their tickets, the ticket date is checked first. The ticket checker ensures that passengers are sitting as per seat allotment. If both of these things are correct then the ticket checker allows a passenger to travel its journey else necessary recommendations are made. To handle real-time conditions, bus service is divided into two types (regular and special). A regular bus service has a fixed pre-defined

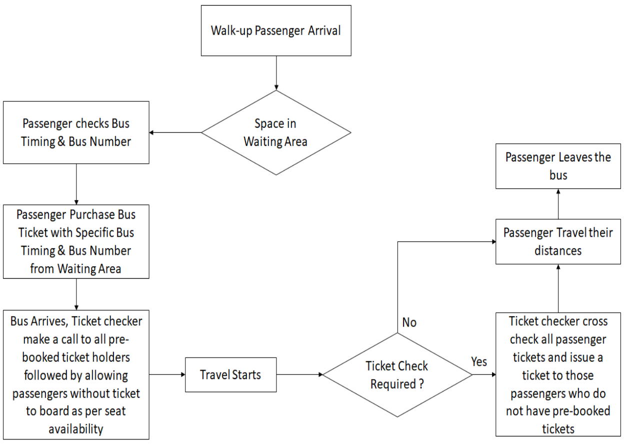

FIGURE 3. Passenger logic flow diagram

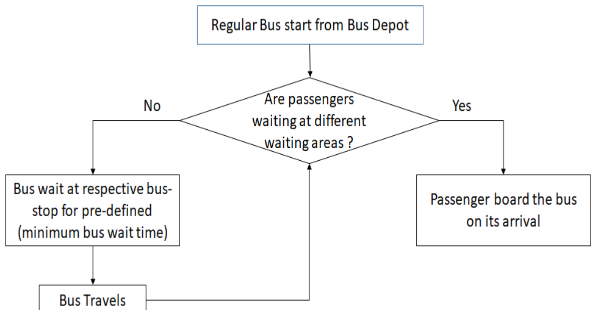

FIGURE 4. Regular bus logic flow diagram.

schedule and it works as shown in figure 4. Whereas, a special bus starts its journey when IoT enabled network signals passengers overload at multiple bus-stops. The special bus logic flow diagram is shown in figure 5. In this case, a special bus is arranged to travel over a specific route as indicated by the IoT network. Quantity of special buses on-road may vary as per routes and number of passengers.

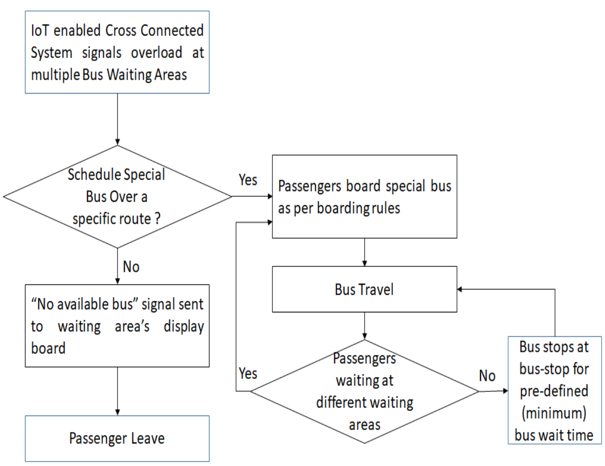

FIGURE 5. Special bus logic flow diagram.

In the electric bus recharging process flow, a bus is charged as a regular electric vehicle at either the bus-stops or recharging station available at different spots during

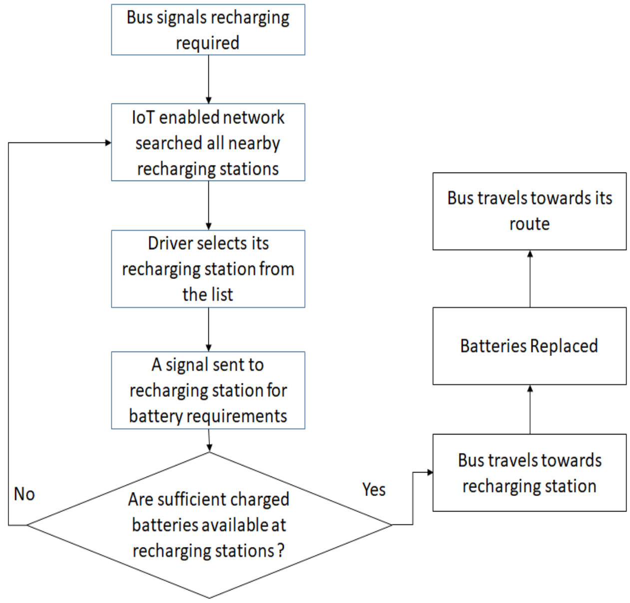

FIGURE 6. Electric bus recharging process flow.

normal conditions. In a recharging station-based system, if the bus meter indicates recharging required then a recharging process flow is executed with the help of the IoT network as shown in figure 6. All nearby recharging stations are searched with the help of the IoT network. A distance-wise sorted list of recharging stations is made available to the bus driver. The driver selects one recharging station and a signal is sent to the recharging station for confirming the availability of sufficient charged batteries. If the recharging station confirms the availability then the bus moves towards recharging station else driver have to select an alternative recharging station. Figure 7 shows the recharging station process flow in detail. Recharging stations put all available batteries on-charge and wait for a signal from a bus.

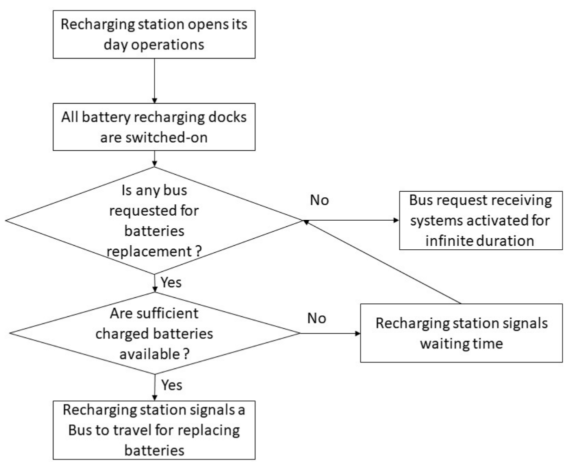

FIGURE 7. Recharging station process flow.

Figure 8 shows the battery delivery system process flow in detail. Here, the scooter is made available to each recharging station for delivering batteries at a remote location.

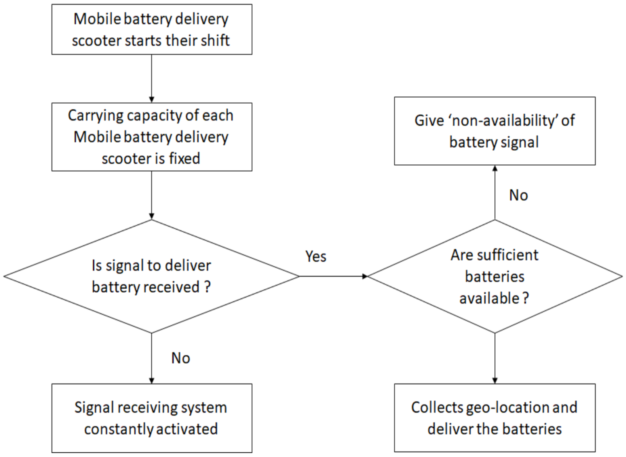

FIGURE 8. Battery delivery system process flow.

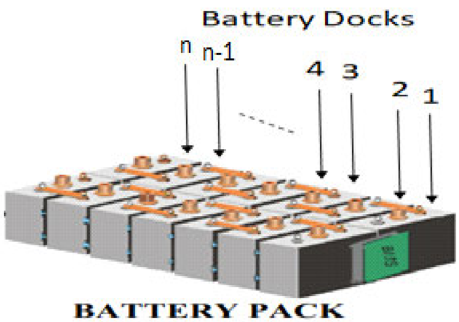

FIGURE 9. Battery pack and battery dock system in buses.

This service is valuable for congested areas where there is the maximum probability of frequent traffic jams or remote areas where recharging stations are not feasible or currently not deployed. In these circumstances, scooters (having fixed battery carrying capacity) can travel to deliver batteries. This system collects geolocation of requesting party and delivers batteries if sufficient charged batteries are available else it signals 'non-availability'. Electric bus design considered in this work is having a regular electric bus charge option with an addition that the whole battery pack is divided into multiple battery docks as shown in figure 9. Here, it is assumed that battery design is hybrid and battery docks are replaceable [21], [44]. This hybrid design provides the flexibilities to distinguish the complete battery pack into smaller size battery docks which can be replaced. As discussed, the battery docks (usually up to 100 kg) can be swapped in emergency cases such as unpredictable bus stops for a longer duration (e.g. heavy traffic).

IV. PROPOSED SIMULATION-OPTIMIZATION APPROACH

This section explains the simulation-optimization approach proposed for the bus public transportation system. In the bus public transportation system, there are many subsystems. In this work, a methodology for charging point allocation, bus schedules, and IoT and cloud network performance optimization has been proposed using simulation optimization. Simulation optimization is necessary for selected problem areas because of uncertain and complex challenges. These challenges include limited charging facility, traffic conditions, and uncertain jams, uneven traffic light stoppage times, passenger demands, on-road bus's dynamics, random passenger loads, frequent changing IoT devices connectivity and storage at a cloud. Here, simulation optimization is fruitful for detailed analysis and analyze the results necessary to understand the real-life system performance.

A. SIMULATION OPTIMIZATION MODEL FOR ELECTRIC BUS SYSTEM

This sub-section formalized the simulation-optimization objective function for the bus public transportation system. Electric bus system performance criterion F with n-parameters $(x_1, x_2, \ldots, x_n)$ is defined as follows:

$$F = f(x_1, x_2, \ldots, x_n) \tag{1}$$

Here, $f()$ is the objective function and $\{x_1, x_2, \ \ldots, x_n\}$ are the parameters that influence the system efficiency in first evaluation and system performance in its second evaluation. Here, two evaluations (system efficiency and system performance) are considered for analysis. In system efficiency, sub-systems integrity is cross-verified whereas system performance measures the quality of service (QoS) parameters for networks in the system. In electric bus system efficiency optimization, quantity F is the objective function categorized as:

$$minimizeF = f(x_1, x_2, x_3) \tag{2}$$

and

$$maximizeF = f(x_4, x_5, x_6) \tag{3}$$

Eqn. (2) and Eqn. (3) are modified if Euclidean space is considered having entries for independent variables and their dependent variables. Modified equations in n-dimensional Euclidean space are written as:

$$minimize\ F = f(x) \quad \text{for } x \in E^n \tag{4}$$

and

$$maximize\ F = f(x) \quad \text{for } x \in E^n \tag{5}$$

Eqn. (4) and Eqn. (5) are modified version of Eqn. (2) and (iii) respectively in n-dimensional Euclidean space (E^n). To selectively implement a simulation-optimization approach in multiple subsystems, two categories of scenarios are formulated: passenger-buses scenarios and IoT network scenarios. These classifications of scenarios are discussed in detail as follows:

Passengers-Buses Scenarios: Dehradun is a city located in the Doon Valley and over the foothills of the Himalayas. Many of the city's places are having deep gorges, low-temperature conditions, many rivers and canals with bouldery beds, frequent high-speed wind flows at different locations, risks of landslides etc. These conditions expect a highly efficient electric battery based bus transportation system. The simulation-optimization model consider the bus's on-road speed, the grade of roads (road's steepness) and the charger's charging capacity. The proposed electric bus system is a non-linear simultaneous simulation optimization model where the performance of different sub-systems is taken into consideration for optimization. In this scenario, simulation-optimization is suggested to be applied for different conditions with the help of objective function. For example, how bus routes can be optimized such that passengers overload at a single bus-stop can be accommodated with multiple buses traveling from different routes. This will maximize bus utilization as well. Similarly, the optimization process is necessary to prioritize the pre-booked ticket system or day-board passes. In detail, various sub-system considered are explained with optimization function as follows:

- $f(x_1)$ is an optimization function to maximize passenger travel during regular bus system implementation and without special or charted bus requirements. This problem statement can be formulated using resource-constrained simulation optimization. Let B_{ij} represents the availability of buses from i^{th} station to the j^{th} station. Now, suppose the number of passengers interested to use the bus service from i^{th} station to the j^{th} station is represented with P_{ij}. Thus, total buses usage (P_{Total}) over the electric bus network from i^{th} station to the j^{th} station is computed as:

$$P_{Total} = \sum_{i=1}^{T_{SS}+T_{DS}} \sum_{j=1}^{T_{SS}+T_{DS}} P_{ij}B_{ij} \tag{6}$$

  Here, T_{SS} and T_{DS} represents the total number of source and destination bus stations available in the electric bus network respectively. Further, constrained formalized over this objective function can be formalized as follows:

  ➢ *Maximum passengers per bus constraint*: According to this constraint, the maximum passengers allowed in j^{th} bus from all i^{th} bus stops (source or intermediate) should be less than or equal to O_i (a threshold limit) i.e.

$$\sum_{i=1}^{T_{BS}} P_{ij} \leq O_i \text{ Where, } j \in \{1, 2, \ldots, T_{buses}\} \tag{7}$$

  Here, T_{BS} is the total number of bus stops (source and intermediate) and T_{buses} is the total number of buses.

  ➢ *Minimum passengers per bus constraint*: There is no such constraint over any route and every bus has to travel as per its schedule. However, a monitoring constraint is put over every bus i.e. if no ticket is issued for a specific bus during a fixed interval then the bus is canceled in the regular category and run in special service only.

- $f(x_2)$ is an optimization function to maximize the utilization of buses during its travel and $f(x_3)$ is an optimization function to maximize the utilization of the pre-booked ticket system for better planning. This is the transportation problem in optimization. To formulate this problem, let us assume that seats $s_1, s_2, s_3, \ldots, s_m$ of one or more buses are available to passengers at distinct locations. These seats are to be occupied by n-passengers that may require one or more seats to be reserved. Assume that the cost of a single-seat ticket is lesser than an on-spot ticket and it is represented as c_{ij} from i^{th} bus stop to j^{th} bus stop. Here, $i \in \{1, 2, \ldots, m\}$, $j \in \{1, 2, \ldots, n\}$, m is the total number of seats and n is the total number of passengers. This transportation problem defines the problem statement to find the quantity P_{ij} with pre-booked tickets from i^{th} bus stop to j^{th} bus stop so as to minimize the bus waiting time at the bus stop and maximize the utilization of buses during its travel. Both of these goals can be achieved if the total cost of transportation using pre-booked tickets (C_{Total}) can be maximized, i.e.,

$$\text{maximize } C_{Total} = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}P_{ij} \tag{8}$$

There are several constraints to the problem defined in Eqn. (8). First, each bus can provide only a fixed quantity of the seats, hence

$$\sum_{j=1}^{n} P_{ij} = s_i \quad \text{for } i \in \{1, 2, \ldots, m\} \tag{9}$$

Second, the number of seats to be reserved from a specific source to a specific destination has to meet the need of passengers traveling i.e.

$$\sum_{i=1}^{m} P_{ij} = b_i \quad \text{for } j \in \{1, 2, \ldots, n\} \tag{10}$$

Here, $b_1, b_2, b_3, \ldots, b_n$ are the pre-book online ticket requirements for n-destinations. Besides, the number of passengers P_{ij} are nonnegative and thus,

$$P_{ij} \geq 0 \quad \text{for } i \in \{1, 2, \ldots, m\} \text{ and } j \in \{1, 2, \ldots, n\} \tag{11}$$

If vector representation of this transportation problem parameters is defined as:

$$\begin{aligned}
\mathrm{c} &= [c_{11}, \ldots, c_{1n}c_{21}, \ldots, c_{2n} \ldots c_{m1}, \ldots, c_{mn}]^T \\
\mathrm{p} &= [P_{11}, \ldots, P_{1n}P_{21}, \ldots, P_{2n} \ldots P_{m1}, \ldots, P_{mn}]^T \\
\mathrm{b} &= [s_1 \ldots s_m b_1 \ldots b_n]^T \\
\alpha &= \begin{bmatrix} 0\,0\,0\,0 \ldots 0\,0\,0\,0 \ldots 1 \\ 0\,0\,0\,1 \ldots 1\,0\,1\,0 \ldots 0 \\ 1\,0\,1\,1 \ldots 1\,0\,1\,0 \ldots 0 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ 0\,0\,0\,1 \ldots 1\,0\,1\,0 \ldots 1 \end{bmatrix}
\end{aligned}$$

Here, α vector shows seat allocation in multiple buses. In this vector, if the seat is pre-booked using the online system then the corresponding bus's seat value is set to 1 else 0. Thereafter, the maximum transportation problem can be re-defined as:

$$\text{maximize } C_{Total} = c^T p \text{ with } \alpha.p = b \text{ and } p \geq 0 \tag{12}$$

Further, $c^T.p$ is the inner product of c and p. The re-stated transportation problem statement in Eqn. (12)

fits into the standard optimization problem. Both of the objective functions of this transportation problem are linear thus, the problem is also known as a linear programming problem in simulation optimization.

- $f(x_4)$ is an optimization function to maximize the utilization of charging points. This work measures the utilization from the charging rate with the assumption that if the charging rate will be higher then maximum buses can take advantage of charging points at different locations. In the proposed system, it is assumed that the charging station has a full-time electric supply. However, keeping the electric failures into consideration charging rate is computed from the charge available. Here, the charge available will be full if it is regular electric supply else it will be dependent over the backup electric system that is not constant or full. Let $Z_{current}$ is the measure of charge available to each charging station at the start of the day. Now, charging rate I is a function of the amount of charge available with each charging station and number of buses (N_{buses}) required charging, i.e.,

$$I = f(N_{buses}, Z_{current}), \quad \text{Where } N_{buses} \in \{1, 2, \ldots, l \tag{13}$$

Here, l represents the maximum value of buses. For each of the unique bus's charge session is defined in the set as $K = (1, 2, \ldots, k)$. Using charge session, charge rate I can be re-computed as:

$$I_k = \frac{V_k}{T_k} \tag{14}$$

Here, V_k is the battery Ah (ampere-hour) and T_k is the charger to bus connection time in k^{th} charging session. Further, the maximum charge rate for each bus is calculated as:

$$I^{max}_{n \in N_{buses}} = maximize\left(\frac{V_k}{T_k}\right), \quad \text{Where } k \in K \tag{15}$$

Each charge station's charging rate of all charging sessions can be evaluated using Eqn. (13) and (15) as:

$$I_k = \begin{cases} f\left(N_{buses}, Z_{current}\right), & if\ f\ f(N_{buses}, Z_{current}) \\ & \geq I^{max}_{n \in N_{buses}} \\ I^{max}_{n \in N_{buses}}, & if\ f\ f(N_{buses}, Z_{current} \\ & < I^{max}_{n \in N_{buses}} \end{cases} \tag{16}$$

Finally, the charge time can be computed from new I_k value using Eqn. (16) as:

$$T_k = \frac{V_k}{I_k} \tag{17}$$

In simulation optimization, the objective is to maximize I_k with minimum T_k to achieve the desired objective function goal.

- $f(x_5)$ is an optimization function to minimize costs involved in deployments of physical infrastructure required to operate the public transportation system. In this optimization function, costs involved in multiple entities (Industry 4.0 infrastructure, charging points, batteries, and buses) can be minimized in the feasible cost region R of the problem defined in Eqn. (4) using local and global constrained minimizers. In local constrained minimizer problem, the set of entities {e: $||e - e^*|| \leq \delta$ with $\delta > 0$ is said to be the ball centric points w.r.t entity e^* such that the minimized cost should be close to $C_{e^*} = B_{e^*} \cap \mathcal{R}$ and it should be nonempty. Here, B_{e^*} is the actual cost for an entity e^*. Finally, $f(x_5, e^*) = \min\{f(x_5, e) : e \in C_{e^*}\}$. In global constrained minimizer problem, the entity e^* is a global constrained minimizer of the problem defined in Eqn. (4) if $e^* \in \mathcal{R}$ is nonempty and $f(x_5, e^*) = \min\{f(x_5, e) : e \in \mathcal{R}\}$.
- $f(x_7)$ is an optimization function to minimize passenger's waiting time at the bus depot and/or bus stops. This task can be started with mathematical traceability for the passenger's waiting time in different source to destination travel pairs [11]. Initially, the cumulative number of passenger's arrival at i^{th} source towards j^{th} destination in time $t \in \{t_1, t_2, \ldots, t_n\}$ can be calculated as follows:

$$P_{ij}(t_2) = \sum\nolimits_{t'=0}^{t} P_{ij}\left(t'\right) \tag{18}$$

Eqn. (18) and other properties can be derived from the plot shown in figure 10. For example, Passengers who board a bus at i^{th} bus-stop and heading towards j^{th} bus-stop can be calculated as follows:

$$P_{ij}(t_3) - P_{ij}(t_1) = \sum\nolimits_{t' \in [t_3, t_3)}^{t} \tau_i \tau_j P_{ij}\left(t'\right) \tag{19}$$

Here, τ_i and τ_j are the binary constants for source and destination bus-stops. These constant can have a value 1 if the bus stops at i^{th} or j^{th} point else 0. In the bus public transportation system, passengers queue at bus stops and travel in the bus scheduling problem. This generates a linear programming problem challenge and the cumulative number of departure passengers from i^{th} bus stop to j^{th} bus-stop can be calculated as:

$$P_{ij}(t_2) = \begin{cases} P_{ij}(t_2 - 1)\ if\ ft_1 \leq t_2 < t_3 \\ P_{ij}(t_2 - 1) + P_{ij}(t_3) - P_{ij}(t_1)\ if\ ft_2 = t_3 \end{cases} \tag{20}$$

Total passenger waiting time at i^{th} bus stop towards j^{th} bus-stop boarding the next bus can be calculated using Eqn. (21).

$$\sum\nolimits_{t \in [t_3, t_3)}^{t} [P_{ij}(t) - P_{ij}(t_1)] = \sum\nolimits_{t \in [t_3, t_3)}^{t} P_{ij}(t).(t_3 - t) \tag{21}$$

Next, the objective of $f(x_7)$ can be mathematically written for S-(source-destination) bus stop pairs as shown in Eqn. (22).

$$minimize \sum\nolimits_{i=1}^{S-1} \sum\nolimits_{j=i+1}^{S} \sum\nolimits_{t \in [t_3, t_3)}^{t} \tau_i \tau_j P_{ij}(t).(t_3 - t) \tag{22}$$

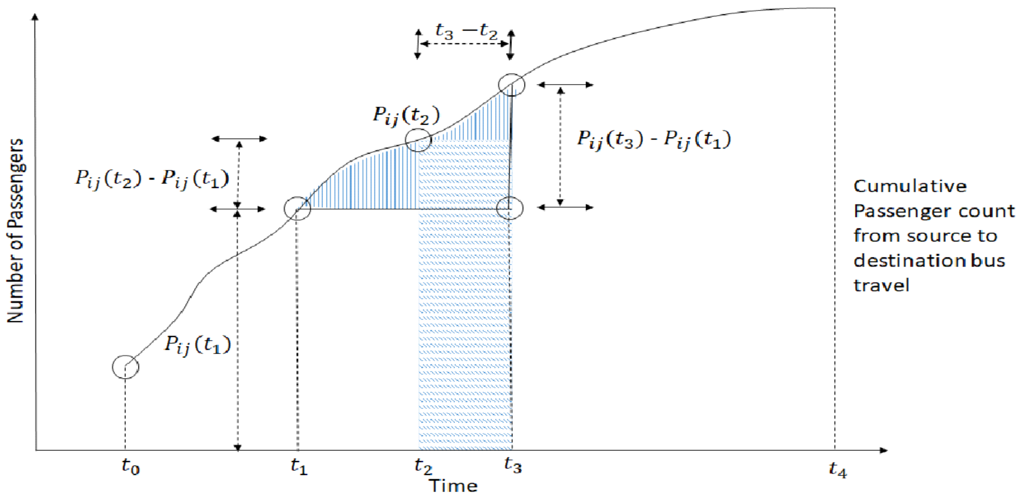

FIGURE 10. **Source station cumulative arrival and departure flow measures in bus public transportation system.**

Additionally, various constraints could be added to the property shown in Eqn. (22) such as:

- Each bus has a limited passenger-carrying capacity. Thus, if there is a shortage of seats for passengers at any bus-stop then waiting time increases.
- Multiple buses schedule linkage can also increase or decrease the waiting time. If a passenger wishes to travel to a route over which one has to change the bus for the journey then the prediction of multiple bus linkage is important. This is because it may increase or decrease the passenger's waiting time.
- Bus travel and stoppage time should have an upper threshold limit to reduce the passenger waiting time else it can also elongate passenger's waiting time.

IoT Network Scenarios: In the proposed system, electric buses are proposed to be interconnected with resource-constrained wireless sensors and constitutes an IoT network. The applications of the electrified bus system, interconnected in an IoT and cloud network, is to provide updated information for passengers and overall system monitoring. The major objective of designing an IoT network scenario is to measure the QoS parameters for the backbone (IoT and Cloud) network. Further, these measures are used in system failure or attack indications followed by objective function updation accordingly. QoS constrained simulation optimization objective function can be mathematically formalized with network parameters such as bandwidth, delay, throughput etc. For example: suppose ϑ_{ij} and θ_{ij} represents the bandwidth utilization and its cost from i^{th} source node to the j^{th} destination node respectively. The total network bandwidth utilization cost can be computed as follows:

$$\theta_{network} = \sum_{i=1}^{\omega_{source}+\omega_{intermediate}+\omega_{destination}} \sum_{j=1}^{\omega_{source}+\omega_{intermediate}+\omega_{destination}} \theta_{ij}\vartheta_{ij} \tag{23}$$

Here, ω_{source}, $\omega_{intermediate}$ and $\omega_{destination}$ are the total number of source, intermediate and destination nodes actively participated in network activities respectively.

Various constraint to bandwidth optimization objective function are as follows:

- *Maximum bandwidth per stakeholder constraint:* In the proposed system, passengers, employees, and devices are the stakeholders of bandwidth consumption. According to the maximum bandwidth per stakeholder constraint, every stakeholder can not be given unlimited bandwidth consumption rights because of congestion control and improving the quality of service. Thus, there should be an upper threshold to limit bandwidth consumption per stakeholder.
- *Minimum bandwidth per stakeholder constraint:* To ensure availability of the network, its resources, and services, it should be ensured that every stakeholder must be a minimum bandwidth consumption rights in any circumstances.
- *Maximum (bandwidth-delay product) BDP per connection constraint:* In the proposed IoT network, BDP per connection is acceptable if throughput between any two ends maintains a ratio of transmission protocol's buffer size and round trip time. Further, the transmission protocol's window size should be greater than the BDP product.
- *Minimum BDP per connection constraint:* Minimum BDP is helpful in attack detection. Thus, a minimum threshold limit is necessary to ensure the proper functioning of the network and its services.
- *Maximum BDP per network constraint:* Like BDP per connection, BDP per network collects the BDP value for all connections in the network. Maximum BDP per network ensures the network is not congested or overloaded with traffic. Thus, a maximum of BDP per network constraint is necessary.

- *Minimum BDP per network constraint:* Likewise, minimum BDP per network constraint protects the network from various attacks.
- *Minimum and maximum inflow rate per node:* Each node has a limited capacity to accept the incoming packets. A maximum and minimum inflow rate are necessary to set because it avoids attacks, and lesser chances of packet drop and/or delay. If the inflow rate is higher than the node's packet processing capacity then there are chances of denial of services. Similarly, if the inflow rate is below a minimum threshold value then the node is ideal and it is not taking part in network activities (routing, forwarding etc.) as well.
- *Minimum and maximum outflow rate per node:* In simulation optimization-based objective function design, it is necessary to set minimum and maximum outflow rate per node for avoiding congestion and network overflow. Further, every node should not be allowed to generate an infinite amount of traffic or sit ideal. Thus, a minimum and maximum outflow rate per node are necessary to set.

In order to execute the simulation-optimization process as per the modified objective function, the cost analysis based bandwidth utilization and related QoS parameters are measured across the network using algorithm 1. Algorithm 1 solve the objective function parameter optimization challenge and proposed the desired conditions to achieve the solutions. Algorithm 1 has five functions: Initialization_function(), Gradient_Computation_function(), Line_Search_function(), Contineous_Objective_function() and Output_function Initialization_function() randomly selects a bus and makes it ready to run over the road by disabling the battery charging process. For the desired objective function parameter gradient is computed regularly over a while in Gradient_Computation_function Line_Search_function() comprises of Pre-Computation_function() for initialization and selection of constants, Minmax_Interpolation_function() and Minmax_Etrapolation_function() identifies the minimized or maximized parameter value computation, Line_Search_Output_function() identifies the optimal solution for the selected objective function. Contineous_Objective_function() predicts the next objective function outcomes for next iteration. Finally, Output_function() compiles the selected QoS parameter value for output.

B. ERROR APPROXIMATION DIFFERENCES FOR OBJECTIVE FUNCTION

An approximation is a difference between an exact value and experimental value. Simulation optimization experimentations are subject to approximation discrepancies. The proposed system considers the differences between the real and specified step responses as an approximation error. This approximation error at time t with variable, x is computed as:

$$E\,(x,t) = e\,(x,t) - e(x_0,t) \tag{24}$$

Algorithm 1 Proposed Steepest-Descent Simulation Optimization Algorithm for Optimized Utilization of an Objective Function Parameter

Goal: To minimize or maximize the utilization of the objective function parameter.

Premises: Let B_i, g_i and C_i represents i^{th} bus, its gradient, and descent gradient variant respectively, M^{Bus} and $M^{Charging\_point}$ represent a maximum number of buses and charging point available in the system, a maximum charger's charging time given to a bus is set to T with a time tolerance of $\in_t$, Time tolerance is the duration considered for the switch over, errors (forward, backward or origin), extra stops etc. $\propto_i$ is the descent gradient variant independent search coefficient, x_i is the i^{th} objective function parameter, ρ is the golstein tests parameter satisfying $0 \leq \rho < 1/2$, σ is second Goldstein test parameter satisfying $0 < \sigma < 1$ and $\sigma \geq \rho$, g() and h() are independent search objective functions for interpolation and extrapolation respectively,

1. **For** $i = 1$ to $M^{Charging\_point}$ **do**:
2. Initialization_function()
3. Gradient_Computation_function()
4. Line_Search_function()
5. Contineous_Objective_function()
6. Output_function()
7. **End For**

Initialization_function()

1. **For** $k = 1$ to M^{Bus} **do**:
2. **Select** B_k
3. Initialize T with tolerance $\in_t$ before disabling the battery charging process.
4. Associate B_k with i^{th} charging point.
5. **End For**

Gradient_Computation_function()

1. Compute capacity descent gradient (g_i).
2. Compute capacity desecent variant $C_i = -g_i$.

Line_Search_function()

1. Line_Search_Initialisation_function()
2. **For** k = 1 to M^{Bus} **do:**
3. Pre-Computation_function()
4. Minmax_Interpolation_function()
5. Minmax_Etrapolation_function()
6. Line_Search_Output_function()
7. Find $\propto_k$ such that minimum capacity objective function f($x_k + \propto_k .C_k$) should be used with maximum charging and charging point utalisation.
8. **End For**

Contineous_Objective_function()

1. Set $x_{i+1} = x_i + \propto_i C_i$
2. Compute $f_{i+1} = f(x_{i+1})$

Here, $e\,(x,t)$, $e(x_0,t)$ and $E\,(x,t)$ are the error during current computation, initial computation (with initial variable x_0) and

Algorithm *(Continue)*

Output_function()

1. **If** $||\propto_k .C_k|| <\in_t$ then:
2. Return $x^{optimized} = x_{i+1}$ and $f\left(x^{optimized}\right) = f_{i+1}$
3. **Else**
4. i = i+1
5. Call Gradient_Computation_function()
6. Call Line_Search_function()
7. Call Contineous_Objective_function()
8. Call Output_function()
9. **End If**

Line_Search_Initialisation_function()

1. **For** $k = 1$ to M^{Bus} **do**:
2. Initialize g_i, C_i, x_i using steepest-descent initialisation step.
3. Initialize g(), h(), σ, $\propto_i$ and ρ from golsdtein tests.
4. Initialize lower and upper descent gradient variant independent search coefficient values i.e. $\propto_{lower}= 0$ and $\propto_{upper}= 10^{99}$.
5. **End For**

Pre-Computation_function()

1. Compute lower values of the objective function $f_{lower} = f(x_i+ \propto_{lower} .C_i)$.
2. Compute $f'_{lower} = f(x_i+ \propto_{lower} .C_i)^T .C_i$
3. Randomly pick descent gradient variant independent search coefficient variable value i.e. $\propto_0$
4. Compute initial objective function value $f_0 = f(x_i+ \propto_0 .C_i)$.

Minmax_Interpolation_function()

1. **If** $f_0 > (f_{lower} + (\propto_0 - \propto_{lower}) .f'_{lower})$ **then:**
2. **If** $\propto_0<\propto_{upper}$ **then:**
3. Set $\propto_{upper}= \propto_0$.
4. Compute $\propto'_0=$

$$\propto_{lower} + \frac{(\propto_0 - \propto_{lower})^2 .f'_{lower}}{2*(f_{lower} - f_0 + (\propto_0 - \propto_{lower}).f'_{lower})}$$

5. **If** $\propto'_0< (\propto_{lower} + g(\propto_{upper} - \propto_{lower}))$ **then:**
6. $\propto'_0=\propto_{lower} +g(\propto_{upper} - \propto_{lower}))$
7. **Else If** $\propto'_0< (\propto_{upper} - g(\propto_{upper} - \propto_{lower}))$ **then:**
8. $\propto'_0=\propto_{upper} - g(\propto_{upper} - \propto_{lower}))$
9. **End If**
10. Assign $\propto_0=\propto'_0$
11. Compute $f_0 = f(x_i+ \propto_0 .C_i)$
12. Compute $f'_0 = f(x_i+ \propto_0 .C_i)^T .C_i$
13. **End If**

Algorithm *(Continue)*

Minmax_Etrapolation_function()

1. **If** $f'_0 < \sigma .f'_{lower}$ then do:
2. Compute deviation $\Delta \propto_0 = ((\propto_0 - \propto_{lower}) .f'_0)/(f'_{lower} - f'_0)$
3. **If** $\Delta \propto_0 < g(\propto_0 - \propto_{lower})$ **then:**
4. $\Delta \propto_0 = g(\propto_0 - \propto_{lower})$
5. **Else If** $\Delta \propto_0 > h(\propto_0 - \propto_{lower})$ **then:**
6. $\Delta \propto_0 = h(\propto_0 - \propto_{lower})$
7. **Compute** $\propto'_0=\propto_0 +\Delta \propto_0$
8. Assign $\propto_{lower}=\propto_0$
9. Assign $\propto_0=\propto'_0$
10. Assign $f_{lower} = f_0$
11. Assign $f'_{lower} = f'_0$
12. **End If**
13. Compute $f_0 = f(x_i+ \propto_0 .C_i)$

Line_Search_Output_function()

a. **Return** $\propto_0$ and $f_0 = f(x_i+ \propto_0 .C_i)$

net error respectively. Now, $E(x, t)$ sampled during different timings $t = 0, 1, 2, \ldots, n$ is computed as:

$$E(x, 0) = e(x_0, t) \tag{25}$$

$$E(x, 1) = e(x, 1) - e(x_0, t) \tag{26}$$

$$E(x, 1) = e(x, 2) - e(x_0, t) \tag{27}$$

$$\ldots\ldots\ldots$$

$$E(x, n) = e(x, n) - e(x_0, t) \tag{28}$$

In result, it is observed that approximation error is a relative measure to a sample value $x = x^*$ such that $F(x^*) \approx 0$. Further, a system with relative approximation error satisfying objective function is mathematically considered to lead simultaneous optimization. Further, this will increase the system efficiency as well. The proposed system is simulated for multiple and different durations. Thus, the finite approximation error difference of a variable $'x'$ is computed using Eqn. (29).

$$E\left(x_{(m_1,m_2)}, t\right) = e(x + m_1, 0) - e(x + m_2, 0) \tag{29}$$

Here, m_1 is the minimum approximation error measurement observed during multiple executions and m_2 is the current execution approximation error measurement. Various forms of approximation error differences are computed as follows: Forward approximation error difference (FAED) is computed using Eqn. (30).

$$FAED = \frac{e(x + (m_2 - m_1), t) - e(x, t)}{m_2 - m_1} \tag{30}$$

Backward approximation error difference (BAED) is computed using Eqn. (31)

$$BAED = \frac{e(x, t) - e(x + (m_1 - m_2), t)}{m_2 - m_1} \tag{31}$$

Origin approximation error difference (OAED) due to the presence of both forward and reverse error is computed using Eqn. (32).

$$OAED = \frac{e(x+(m_2-m_1), t)-e(x + (m_1 - m_2), t)}{2*(m_2-m_1)} \tag{32}$$

Algorithm 2 Simulation Annealing and Error Approximation Difference enabled Simulation Constrained Optimization Algorithm

Goal: To avoid noisy and wrong simulation optimization execution with the least error approximation.

1. Initialization_function()
2. ObservationMeasurement_function()
3. ErrorApproximationDifferencesComputation_function()
4. ObjectiveFunctionComputation_function()
5. ConvergenceComputation_function()
6. OutputComputation_function()

Initialization_function()

a. Set number of independent variable count $v_{count} = 0$.
b. Set the priority of independent variables and pick the initial independent variable $x_{initial}$.
c. Using an initial independent variable, compute the initial objective function $F_{initial} = f(x_{initial})$.
d. Assuming zero initial approximation error difference (i.e. e($x_{initial}$,0)≈ 0), update initial objective function using Eqn. (24) is defined in Eqn. (33)

$$E\left(x_{initial}, t_2\right) = e\left(x_{initial}, t_2\right) - e\left(x_{initial}, t_1\right) \quad (33)$$

Here, t_1 and t_2 are the two timings (minimum and current) of error measurements.

ObservationMeasurement_function()

a. Increment $v_{count} = v_{count} + 1$
b. Compute the list of prioritized independent variable list as: $x^T_{v_{count}} = [x_1, x_2, \ldots, x_n]$
c. **For** j =1 to n:
   Compute the changes in x_j using the dependent variable as: $\delta x_j^{T,I} = [\delta x_1^I, \delta x_2^I, \ldots, \delta x_n^I]$
   Compute $x_j = x_{j-1} + \delta x_j^{T,I}$
   For each T in $[t_1, t_2, t_3, \ldots, t_o]$:
   Compute $F_j(x, T) = f\left(x_j, T\right) + \delta F_j\left(x_j, T\right)$ and $\delta F_j\left(x_j, T\right) = F_{j-1}\left(x_j, T\right) - F_j\left(x_j, T\right)$
   End For
   End For

Algorithm *(Continue)*

ErrorApproximationDifferencesComputation_function()

a. Initialize $m_{minimum}$ with minimum approximation error and $m_{current}$ with a recently executed approximation error.
b. For j =1 to n:
   Compute $FAED(j, t) = \frac{e\left(\left(x_j + \left(m_{current} - m_{minimum}\right)\right), t\right) - e(x_j, t)}{m_{current} - m_{minimum}}$
   Compute $BAED(j, t) = \frac{e\left(x_j, t\right) - e\left(\left(x_j + \left(m_{minimum} - m_{current}\right)\right), t\right)}{current - m_{minimum}}$
   Compute $OAED(j, t) = \frac{e\left(\left(x_j + \left(m_{current} - m_{minimum}\right)\right), t\right) - e\left(\left(x_j + \left(m_{minimum} - m_{current}\right)\right), t\right)}{2 * \left(m_{current} - m_{minimum}\right)}$

ObjectiveFunctionComputation_function()

a. **For** j =1 to n:
   If $FAED(j, t)$ is nonzero **then**
   Compute $f\left(x_j, T\right) = F_j(x, T) + FAED(j, t)$
   Where, T ∈ $[t_1, t_2, t_3, \ldots, t_o]$
   If $BAED(j, t)$ is nonzero **then**
   Compute $f\left(x_j, T\right) = F_j(x, T) + BAED(j, t)$
   Where, T ∈ $[t_1, t_2, t_3, \ldots, t_o]$
   If $OAED(j, t)$ is nonzero **then**
   Compute $f\left(x_j, T\right) = F_j(x, T) + OAED(j, t)$
   Where, T ∈ $[t_1, t_2, t_3, \ldots, t_o]$
   End For

ConvergenceComputation_function()

a. Set $j = 1$
b. Set $X = \{x_1, x_2, \ldots, x_n$ with initial value $x_{initial} = x_1$
c. Generate infinite sequence $\{x_j\}_{j=0}^{\infty}$. where $x_{j+1} \in f(x_j)$
d. **If** a solution set φ and a descent function $D(x_j)$ exist **then**
e. **If** $x_j \notin \varphi$ **then**
f. Verify $D(x_{j+1}) < D(x_j)$ Where $x_{j+1} \in f(x_j)$
g. **Else**
h. Verify $D(x_{j+1}) \leq D(x_j)$ Where $x_{j+1} \in f(x_j)$
i. **Return** Pass
j. **Else**
k. **Return** Fail

OutputComputation_function()

a. **Return** $f_{final} = f(x_j)$ Where, x_j is the j^{th} parameter value when it passes ConvergenceComputation_function() test.

FAED, BAED and OAED methods are helpful for simulation optimization if the number of simulation runs is predefined. Although approximation error computations are added to improve system efficiency and reducing the errors but the propose simulation optimization method with approximation error computation is stochastic in nature and it could result in a noisy and wrong execution. In order to avoid noisy and wrong execution scenarios, error approximation is integrated with the proposed simulation objective function using algorithm 2.

Algorithm 2 has size functions:
Initialization_function(),
ObservationMeasurement_function(),
ErrorApproximationDifferencesComputation_function(),
ObjectiveFunctionComputation_function(),
ConvergenceComputation_function()
and OutputComputation_function

Initialization_function() set values for independent variables, computes initial objective function value and set new error value. ObservationMeasurement_function() computes the dependent variables and updates the objective function.

ErrorApproximationDifferencesComputation_function() computes the forward, backward and origin appromiation errors and integrates with objective function. ObjectiveFunctionComputation_function() recomputes the objective function with error approximation taken into consideration. ConvergenceComputation_function() verifies the objective function with error approximation for descent function outcome. If it passes the descent function requirements for simulation optimization with pre-defined output set then final objective function with parameter value is returned using OutputComputation_function().

V. SIMULATION AND RESULT ANALYSIS

This section explains the electric bus system setup and various simulation scenarios. In this work, simulation is created using JaamSim simulator [45]. JaamSim is a free, open-source, discrete event, interactive, drag-and-drop simulation having input/output variation and model development capabilities. As compared to other simulators (including JMT [46], NS-2 [47], NS-3 [48], CupCarbon [49] etc.), JaamSim can model probabilistic distribution, resources, process flows, statistical calculation, fluid objects, and system internal queueing theory-based modeling, programming, and processing capabilities. This makes JaamSim easy-to-use and simulates large and long-duration simulation in a few minutes or hours. A detailed explanation is as follows:

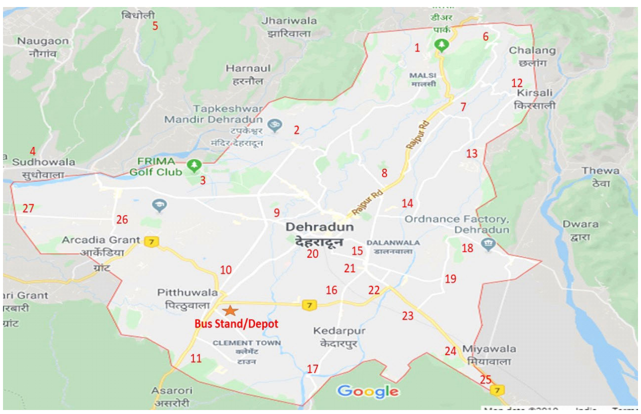

FIGURE 11. Dehradun map and important points for constituting buses routes.

A. ELECTRIC BUS SYSTEM

This section shows the simulation analysis of the proposed approach for Dehradun city. Figure 11 shows the Dehradun map and important points for constituting bus routes. There are in-total 27 points (marked 1-27) identified to decide bus routes. These points are identified in a way that every major region of passenger transportation should be covered. Table 2 shows the bus routes and related information. Here, two types of bus routes are classified: off and normal. Buses run over normal routes during the maximum period of a year. Whereas, off day routes are opened when there are special events in the city. For example, political rallies, military parades, natural disasters, festivals etc. Other parameters shown in table 2 include source station, intermediate station, destination station, route number and route name. A unique route number is formulated using source, intermediate and destination station numbers. The forward and reverse route is named the same but distinguished with a number. For example, A135 is a forward route with source station 1 and destination station 5 followed by an intermediate station 3. Further, A531 is the reverse route of A135. In total, 32 (16 forward and 16 reverse) normal routes are identified. Additionally, 6 (3 forward and 3 reverse) off-day routes are also identified. This data is collected for simulation from google maps. Simulation analysis is performed over seven timings slots as specified in table 3. Early morning, morning-2, afternoon and night are off-peak hours whereas morning-1, evening and late evening are peak hours. Peak and off-peak timings are decided based on passenger' bus requirements.

Figure 12 to figure 14 shows three scenarios (10, 15 and 20 charging points) of deployment of charging points over the city. These charging points are deployment in such a way that every bus route has a uniform distribution of such points. Table 4 shows information regarding charging points including the charger points, charger's power and its availability (in minutes). Further, these charging points are classified into three categories: C1 to C10, C11 to C15 and C16 to C20. C1 to C10 chargers are of high power and deployed in bus depots or over points where there is maximum buses pass through. C11 to C20 are comparatively low power and used at bus stops. C11 to C15 are used for a maximum of 5 minutes whereas C16 to C20 can be used a maximum of 10 minutes. Table 5 shows the detailed route information including bus stops, stop time, traffic lights, average stop time at traffic lights, end-to-end route distance, probability of stoppage at traffic lights, the average number of passengers travel in buses per day and the maximum number of passengers travel per day over different bus routes. This information is necessary to plan various activities in the bus transportation system. Further, this information is used in the next subsection to simulate the system's working using the JaamSim simulator.

B. JaamSim MODEL FOR ELECTRIC BUSES CHARGING ANALYSIS

This subsection simulates the Electric bus charging and its integration with complete working systems. Table 6 shows the battery properties considered for this simulation. Figure 15 shows the proposed electric bus charging model. In this model, there are eight sub-systems (BusGeneratorForCharging, BusSequencer, BusSchedulerForCharging, UniformDistributor, Charger, ChargedBusesInQueue, BusSchedulerForRoute, BusTerminatorFromDepot). Algorithm 3 explains these sub-systems and their integration in detail. BusGeneratorForCharging subsystem simulates the real-time availability of buses in a bus-depot for electric charging. BusSequencer subsystem simulates the collection of bus numbers from buses and their running schedules from records. This information is made available to the BusSchedulerForCharging subsystem.

BusSchedulerForCharging subsystem selects a default charger and set its priority to high and sort other chargers based on their priorities. A default charger is a charger having a minimum failure rate and high charging capacity.

TABLE 2. Dehradun buses routes information.

Sr. No.	Source Station	Intermediate Station	Destination Station	Short Route No.	Route Name	Route Off/Normal Days
1	1	2,3	5	135	A	Normal
2	5	3,2,	1	531	A	Normal
3	1	7,8,9,3	5	195	B	Normal
4	5	3,9,8,7	1	591	B	Normal
5	1	7,8,20,10,26	5	1265	C	Normal
6	5	26,10,20,8,7	1	5261	C	Normal
7	1	2,10	11	1211	D	Normal
8	11	10,2	1	1121	D	Normal
9	1	7,8,20,10	11	12011	E	Normal
10	11	10,20,8,7	1	11201	E	Normal
11	1	7,8,15,21,22,23,24	25	125	F	Normal
12	25	24,23,22,21,15,8,7	1	251	F	Normal
13	6	7,8,20	11	611	G	Normal
14	11	20,8,7	6	116	G	Normal
15	6	7,8,15,21,16	17	617	H	Normal
16	17	16,21,15,8,7	6	176	H	Normal
17	6	7,8,9,3,26	27	627	I	Normal
18	27	26,3,9,8,7	6	276	I	Normal
19	12	13,14,18,19,23,24	25	1225	J	Normal
20	25	24,23,19,18,14,13	12	2512	J	Normal
21	12	13,14,15,21,16	17	1217	K	Normal
22	17	16,21,15,14,13	12	1712	K	Normal
23	12	13,14,15,20,10	11	1211	L	Normal
24	11	10,20,15,14,13	12	1235	L	Normal
25	18	19,15,20,9,3	5	185	M	Normal
26	5	3,9,20,15,19	18	518	M	Normal
27	18	19,15,20,9,3	4	184	N	Normal
28	4	3,9,20,15,19	18	418	N	Normal
29	18	14,9,3,26	27	1827	O	Normal
30	27	26,3,9,14	18	2718	O	Normal
31	18	19,23,22,16	11	1811	P	Normal
32	11	16,22,23,19	18	1118	P	Normal
33	1	8,15,21,16,10,26	5	185	Q	Off-day
34	5	26,10,16,21,15,8	1	581	Q	Off-day
35	6	7,8,1,21,16,10,26	27	6727	R	Off-day
36	27	26,10,16,21,1,8,7	6	2776	R	Off-day
37	1	8,15,21,16,10,26	4	1264	S	Off-day
38	4	26,10,16,21,15,8	1	4261	S	Off-day

TABLE 3. Buses-timing information mapping.

Timing	Time Period
Early Morning	04:00 - 07:00
Morning-1(Peak-1)	07:00 - 10:00
Morning-2	10:00 - 12:00
Afternoon	12:00 - 16:00
Evening (Peak-2)	16:00 - 18:00
Late Evening (Peak-3)	18:00 - 21:00
Night	21:00 - 04:00

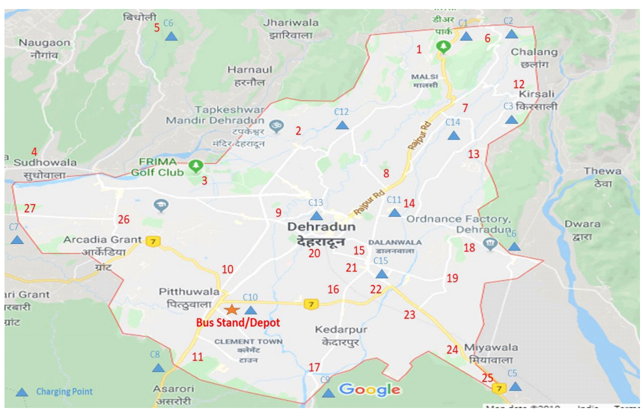

FIGURE 12. Deployment of 10 charging points over the city.

A UniformDistributor subsystem initially distributes the buses based on priorities and, thereafter, uniformly among available and running chargers. The charger sub-system made multiple and parallel charging points available to buses. Each of these chargers has a fixed charging capacity and duration. Handling duration is an additional overhead considered over the charger sub-system for connecting and disconnecting the charging cables. Each of the available chargers makes an

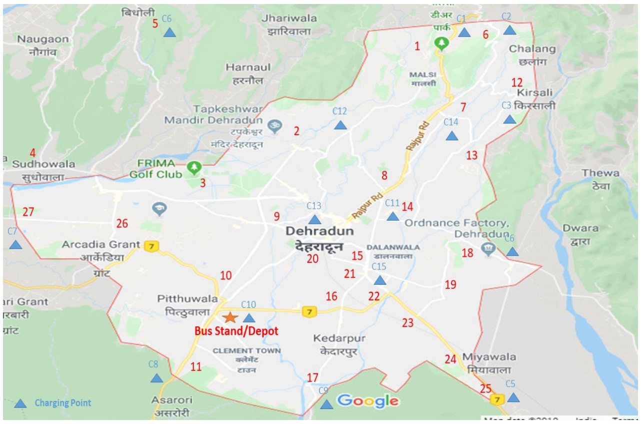

FIGURE 13. Deployment of 15 - charging points over the city.

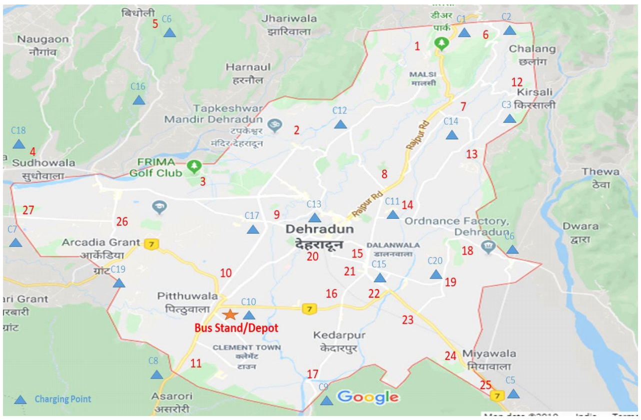

FIGURE 14. Deployment of 20 - charging points over the city.

entry in ChargedBusesInQueue sub-system for those buses whose battery is fully charged, and now they are available to run on their routes. Next, BusSchedulerForRoute sub-system select buses from all ChargedBusesInQueue sub-systems based on their schedule to run on-roads. An exit pass is issued to those buses who are ready to run on-roads. BusTerminatorFromDepot sub-system verifies the exit passes and allows them to leave the bus depot. Detailed simulation parameters for the electric bus charging system are shown in table 7. Further, figure 16 shows the execution screenshot of the proposed electric bus charging system. Figure 17 to figure 25 shows the average, best and worst-case analysis of energy consumption in the proposed system. The total energy consumption is calculated as shown in Eqn. (34)

$$E_{Total} = P_{Total}.\Delta t_{Total} \tag{34}$$

Here, E_{Total}, P_{Total} and Δt_{Total} are the total energy consumption, total power consumption and total time of using the buses. Here, total power consumption is influenced by several factors such as total bus' mass after loading the passengers, the power required by the auxiliary system (including air-condition, sensor devices, multimedia devices, all types of lighting equipment, telematics devices etc.), route profile, increase or decrease in acceleration (computed from gear level), in-vehicle display screens, climate situations, and etc. In this model, it is assumed that there exist components (especially auxiliary systems) whose power consumption is constant over time. Further, Δt_{Total} is the total time spent over the bus trip and dwelling time. Here, the major time component is trip time and it is calculated as shown in Eqn. (35)

$$\Delta t_{Total} = \frac{D_{Total}}{V_{average}} \tag{35}$$

Here, D_{Total} and $V_{average}$ are the total trip distance and the average speed of the trip. D_{Total} is the distance covered with different speeds (low, medium and high accelerations) that are fixed for the model as per random gears opted. The simulation model follows the following sequence of steps in the complete system's energy consumption calculations over simulation time.

- Individual bus operations are calculated. This includes the bus arrival and departure from source to bus depot. In this operation, variable distances, bus trip time, dwelling time etc. are taken into consideration.
- Every individual bus stop-to-stop energy consumption provides total energy consumption (E_{Total}).
- An aggregated energy demand of each bus from day-start to day-off is computed. This provides the energy consumption statistics for each bus route.
- Energy consumption in every bus route is added to the compute the total energy consumption for the overall system simulation time.

The energy consumption calculation takes care of on-road friction levels. In this work, four road friction ranges are set for simulation 0.5 to 0.9, 0.4 to 0.8, 0.2 to 0.3 and 0.1 to 0.2. To map the real-time road conditions with simulation, data is collected through a smart city project plan [8], analyzed and set in the simulator. In this experimentation, the maximum speed allowed to a vehicle in raining reason or road with an elevation greater than 45° or friction range lesser than 0.3 is 25 kms (second gear speed). Now, if elevation lies between 30° to 45° or friction range lesser than 0.8 and it is not a raining season then maximum speed allowed is 50 kms (third gear speed). Further, if road elevation level lies below 30° or friction range between 0.5 to 0.9 and it is not a raining season then maximum speed allowed is 80 kms (fourth gear speed). In the final range, speed can go to 100 kms (fifth gear speed) in case of motorway or highway. In the simulation, friction ranges are already set and it is assumed that if it is raining season then friction range will be 0.2 to 0.3. In the case of road-elevations, each route's number of elevation points are pre-defined and set in simulation.

Figure 17 to figure 19 shows the energy consumption over 100 days around the clock, during peak hours and non-peak hours respectively. Figure 17 shows that energy consumption over different routes lies between 0.4 KWh/Km to 1 KWh/Km. Maximum energy is consumed over route P because of traffic and regional reasons. Figure 18 shows energy consumption during peak hours over 100 days.

TABLE 4. Charging point information.

Charging Point ID	Charger's Power	Maximum Available Time for Charging
C1 to C10	~120 kW to ~240 kW (500-1000V DC Charging)	15 minutes to 360 minutes (11:00 PM-4:00 AM)
C11 to C15	~15 kW to ~20 kW (500-1000V DC Charging)	5 minutes (4:00 AM-11:00 PM)
C16 to C20	~15 kW to ~20 kW (500-1000V DC Charging)	10 minutes (4:00 AM-11:00 PM)

TABLE 5. Route stop time information (in minutes).

Route No.	Number of Bus Stops	Average Stop Time at Bus Stops (minutes)	Number of Traffic Lights	Average Stop Time at Traffic Lights	Route Distance (Km)	Stop Probabilit y at Traffic Lights (Binomial Dist. (%)	Average Number of Passengers Travel in buses per Day	Maximum Number of Passengers Travel per Day (during Peak Hours)
A	10	5	10	3	30.3	44	840	1110
B	25	4	15	4	28.9	61	1150	1420
C	30	4	18	4	30.8	63	1210	1510
D	9	5	9	3	23.6	43	760	990
E	13	4	12	3	25.5	64	980	1120
F	14	4	14	3	21.8	66	1150	1490
G	11	5	11	4	24.0	59	1080	1310
H	11	5	11	4	19.7	59	1240	1560
I	20	4	15	4	31.5	61	1130	1320
J	12	5	9	2	18.8	46	760	910
K	11	5	9	2	21.0	62	990	1120
L	14	5	11	4	20.2	64	980	1310
M	23	4	15	4	38.9	65	1020	1240
N	23	4	15	4	26.9	61	1140	1420
O	24	4	15	4	28.8	43	810	1020
P	19	4	10	4	21.1	57	1060	1310
Q	28	4	17	4	49.8	66	1230	1620
R	28	4	18	4	36.4	68	1190	1610
S	28	4	17	4	43.1	66	1240	1430

TABLE 6. Battery properties for simulation.

Property	Specification
Battery type	Lithium-ion
Maximum charge capacity	450 kWh
Battery voltage system	400 V to 800 V
Battery degradation per year	2.5%
Battery Lifetime	7 years
Battery capacity reserve for battery life	5%
Battery capacity reserve for operational flexibility	10%
Battery Weight	1700 kg (approx.)
Minimum and maximum charging time depending upon charging connection availability	5 to 10 hours
Minimum and maximum energy consumption	1.5 to 2.0 kWh/km

As expected, energy consumption is higher in this case and it lies between 0.8 KWh/Km to 1 KWh/Km. There are multiple routes (C, H J, M and P) over which energy consumption is close to 1 KWh/Km. Figure 19 shows energy

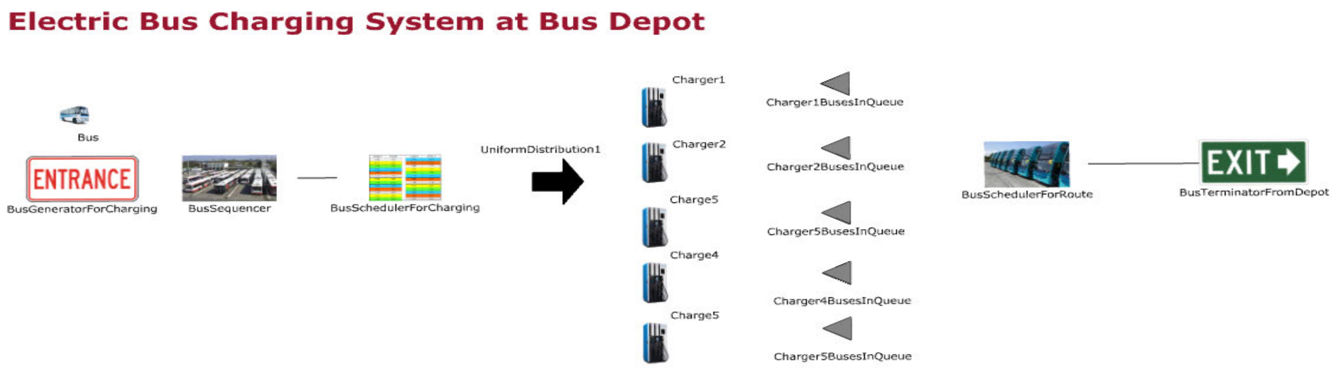

FIGURE 15. **Model for electric bus charging.**

consumption during non-peak hours over 100-days. Results show that energy consumption lies between 0.5 KWh/Km to 0.7 KWh/Km. Similar observations are analyzed over 365 days as shown in figure 20 to figure 22. Figure 20 shows that energy consumption over different routes lies between 0.3 KWh/Km to 1 KWh/Km around the clock. Figure 21 and figure 22 shows that energy consumption over different routes lies between 0.8 KWh/Km to 1 KWh/Km and 0.5 KWh/Km to 0.7 KWh/Km during peak and non-peak hours respectively. Five years of energy consumption trends are shown in figure 23 to figure 25. Results show that energy consumption over different routes lies between 0.4 KWh/Km to 1 KWh/Km, 0.8 KWh/Km to 1 KWh/Km and 0.5 KWh/Km to 0.7 KWh/Km during around the clock, peak and non-peak hours respectively.

Figure 26 shows the comparative analysis of variations in multiple timings parameters with simulation time. Average charger waiting time varies from 0.2 minutes (for 24 hours simulation) to 0.4 minutes (for 1 year simulation). This waiting time includes charger deployed at different locations across the city. Average route scheduler waiting time for any bus after charging varies from 0.48 minutes (fr 24 hours) to 0.92 minutes (for 1 year). This scheduling includes re-routing in case of traffic-congestion or change in natural conditions (e.g. heavy raining, tree falling, landslide etc.). Average queue waiting time in the system varies between 0.49 minutes (for 24 hours) to 0.91 minutes (for 1 year). This is the waiting time at traffic lights or over traffic road situations. Average scheduler time for charged bus is the time to schedule the bus to run over the road with pre-defined and specific routes. Once a bus battery is charged, it is available to run over the road. Thus, a plan is required to assign a route to bus. Time taken to schedule this activating is the scheduler time. Average scheduler time for charging varies from 0.003 minutes (24 hours) to 0.42 minutes (for 1 year).

C. JaamSim MODEL FOR PASSENGERS BOARDING ELCTRIC BUS

Figure 27 shows the JaamSim model to simulate passenger boarding bus, bus arrives at the bus stop, passenger wait area, bus travel on its route and its performance before a passenger leaves a bus. Total simulation is divided into multiple time slots (24h, 48h, 96h, 192 h) for their analysis. Figure 28 shows the comparative analysis of the average passenger's waiting time in the waiting area. Results show that this time varies between 0.18 minutes (for 24 hours) and 0.54 minutes (for 1 year). This waiting time is lower for small duration simulation but increases with an increase in simulation time because the simulation-optimization approach considers different pre-defined constraints into consideration. Figure 29 shows the comparative analysis of average passenger's total time in the system with an increase in on-road traffic. Real-time on-road traffic data is considered from official data available over Dehradun smart city design [8]. Results show that average passenger time in the system varies from 41.6 minutes (for 24 hours) to 45.5 minutes (for 1 year) when on-road traffic varies between 0.4 million to 0.5 million vehicles. This time measurement varies from 74.4 minutes(for 24 hours) to 78.6 minutes (for 1 year) and 96.6 minutes (for 24 hours) to 100.7 minutes (for 1 year) for on-road traffic between 0.5 million vehicles to 0.75 million vehicles and 0.75 million vehicles to 1 million vehicles respectively. As expected, higher on-road traffic increases system constraint which in-turn increases passenger's time.

D. COMMUNICATION AND COMPUTATIONAL COSTS ANALYSIS

In this section, the complexities in implementing the proposed approach are computed and compared with the state-of-the-art. In an efficient system design and implementation, sensors/devices are programmed to exchange the necessary information without impacting the quality of service. Thus, the cost complexities required to implement the proposed logic are dependent on resource availability. Here, two cost complexities (communication and computational) are computed to analyze the hardware requirements to implement the proposed logic. The communicational cost computes the hardware requirements for transmitting and propagating the data. Whereas, computational cost involves the hardware requirements for processing the data at any device.

Algorithm 3 Proposed Electric Bus Charging and Route Information Integration Algorithm

1. Set Simulation Time to Real Time Execution Factor
2. Set Simulation's Pause Time
3. **While** Real Time Expires:
4. BusGeneratorForCharging_Function()
5. BusSequencer_Function()
6. BusSchedulerForCharging_Function()
7. UniformDistributor_Function()
8. Charger_Function()
9. ChargedBusesInQueue()
10. BusSchedulerForRoute_Function()
11. BusTerminatorToDepot_Function()
12. **End** While

BusGeneratorForCharging_Function()

a. Set FirstArrivalTime = 0 seconds
b. Set InterArrivalTime = 10 minutes
c. Set EntititesPerArrival = 1
d. **While** SimulationTimeExpires:
e. Apply NormalDistribution Model and Generate Buses for Bus Sequencer
f. **End While**

BusSequencer_Function()

a. SetAttributeAssignmentList to Bus Number
b. Create an empty queue list
c. **For each** Bus Number:
d. **If** no bus in charging queue:
e. Assign bus to BusSchedulerforCharging
f. **Else**
g. Add Bus Number to queue list
h. Assign queue list to BusSchedulerforCharging
i. **End If**
j. **End For**

BusSchedulerForCharging_Function()

a. Set default charger
b. Set priorities of all available chargers
c. **For each** entry in queue list:
d. Extract bus number
e. Pick bus schedule of selected bus number
f. Sort buses as per their bus schedules
g. Assign bus to uniform distributor with default charger and charger's priority values
h. **End For**

Algorithm *(Continue)*

UniformDistributor_Function()

a. Set Minimum Distribution Value to 5 minutes
b. Set Maximum Distribution Value to 10 minutes
c. Set a list of chargers as per their priorities
d. Set flags of each charger to OFF
e. **For** each charger in charger list:
f. **If** charger's flag is OFF
g. Assign bus to charger
h. Set flag of charger to ON
i. **Else**
j. Put bus in waiting queue
k. **End If**
l. **End For**

Charger_Function()

a. Measure battery state
b. **If** battery is CHARGED:
c. Indicate bus to move to BusSchedulerforRoute
d. **Else**
e. Indicate time required to charge the battery
f. Start battery charging
g. **End If**

ChargedBusesInQueue()

a. Make a queue of each charger
b. Make a (Charger, Priority) tuple for each charger
c. Sort (Charger, Priority) tuple according to its priorties
d. **For** each (Charger, Priority) in sorted tuple:
e. Pick its charged bus
f. Assign to BusSchedulerfor Route
g. **End For**

BusSchedulerForRoute_Function()

a. Make a queue of each Charged Bus
b. Prepare (Route, Top Queue Charged Bus) charter
c. Assign Route travel timing chart with(Route, Top Queue Charged Bus) charter to driver
d. **For** each (Route, Top Queue Charged Bus, Timings) in sorted tuple:
e. Pick Bus Stop and Bus Schedule
f. Assign to Bus Scheduler to Bus Stop
g. **End For**

BusTerminatorToDepot_Function()

a. Fetch a list of all buses
b. **For** each bus in Bus List:
c. Mark it route completed
d. Assign a parking slot in Bus Depot
e. **End For**

Gate Equivalents (GEs) measures the area occupied by a two-input drive-strength-one NAND gate in the implementation of the required concept. GEs can be used to measure the communicational and computational complexities of digital circuits used in concept implementation [50]. Figure 30 and figure 31 shows the comparative GE analysis for communication and computational costs. Figure 30 shows a comparative analysis of the number of GEs required for the proposed approach with other [51]. The result shows that the proposed approach requires a minimum number of GEs in its implementation with and without security primitives. Security primitives considered in this work for analysis include availability, confidentiality, and authentication. Here, those security primitives are taken into consideration that requires less than 1000GEs [52]. Availability security primitive is used here to protect the network from Denial-of-Service (DoS)

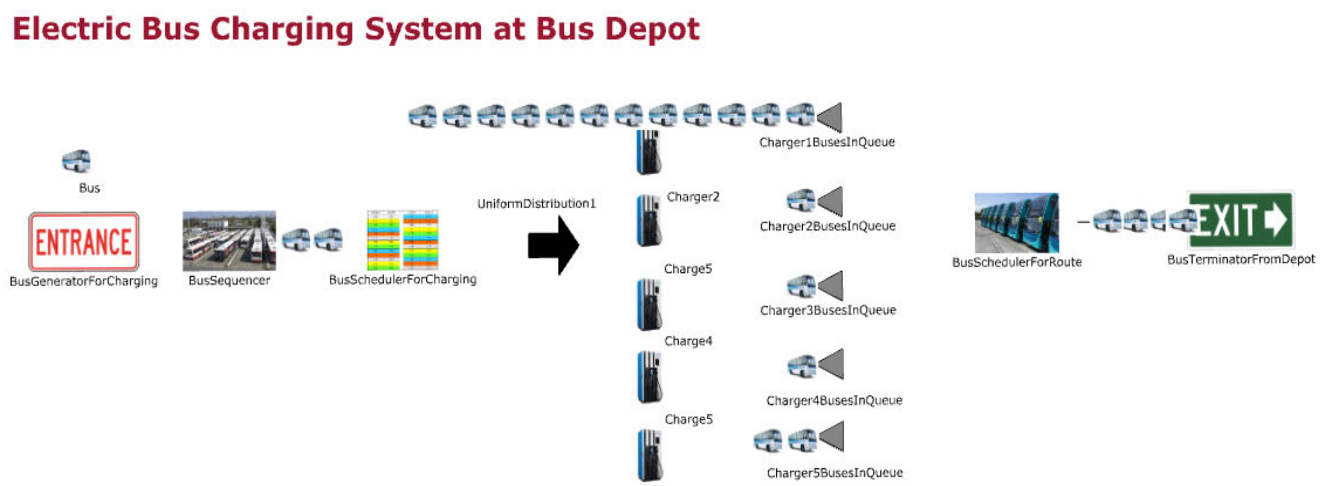

FIGURE 16. Execution screenshot of electric bus charging system.

TABLE 7. Simulation parameters for electric bus charging system.

Parameter	Value
Simulator	JaamSim
FirstArrivalTime	0 second
InterArrivalTime	10 minutes
EntititesPerArrival	1
Working StateList	[Wait Move Charging Malfunction]
AttributeAssignmentList	Bus Number
TravelTime (between Bus Arrival and Assign to Charger)	120 seconds
StateAssignment (between Bus Arrival and Assign to Charger)	Move
Default Charger	Charger 1 (150 KW)
TargetComponentList for Charging	[Charger2 Charger3 Charger 4 Charger5]
Chargers Capcacity	Each charger has a charging capacity of 150 KW
Minimum Uniform Distribution Time	15 seconds
Maximum Uniform Distribution Time	25 minutes
Mode Value of Uniform Distribution Time	10 minutes
Charger's StateAssignment	[Idle Charge Malfunction]
BusSchedulerforRoute Service Time (including issuing exit pass)	30 seconds
WaitQueueListprioritywise (initially)	[Charger1BusesInQueue Charger2BusesInQueue Charger3BusesInQueue Charger4BusesInQueue Charger5BusesInQueue]
BusTerminatorFromDepot's Service Time (including travel and exit pass checking)	15 seconds

attack, encryption/decryption is used to ensure confidentiality of data communication between any two ends and Hashing with Message Authentication Code (HMAC) is used to ensure message authentication, compression and collision resistance. Although the number of GEs required with security primitives increases when availability, confidentiality, and authentication are ensured, but it is lesser for the proposed approach compared to existing [51]. Similarly, comparative computation cost analysis is shown in figure 31.

The communication and computational costs will remain intact if the hardware used to propagate, transmit and process the data meeting that requires (i) the reusability rate of hardware equipment should not be reduced over time, (ii) the security primitives and protocols should be of lightweight in nature rather than using traditional primitives and protocols, and (iii) there should not be use or reuse of same hardware for security and normal data processing because this will not meet the security objective function requirements.

FIGURE 17. 100-days energy consumption over routes (around the clock).

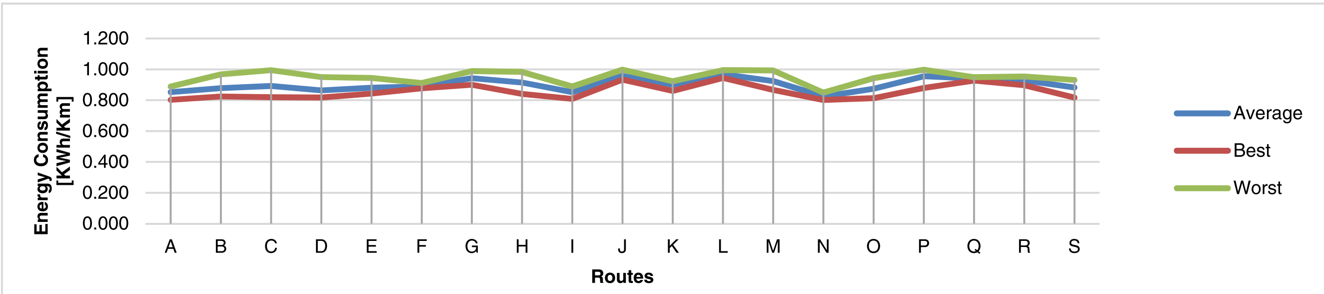

FIGURE 18. 100-days energy consumption over routes during peak hours (peak-1, peak-2 and peak-3).

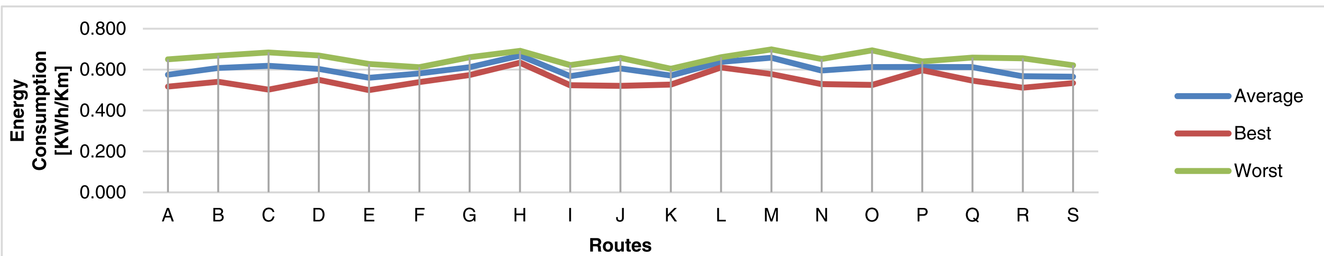

FIGURE 19. 100-days energy consumption over routes during normal hours (early morning, morning-2, afternoon and night).

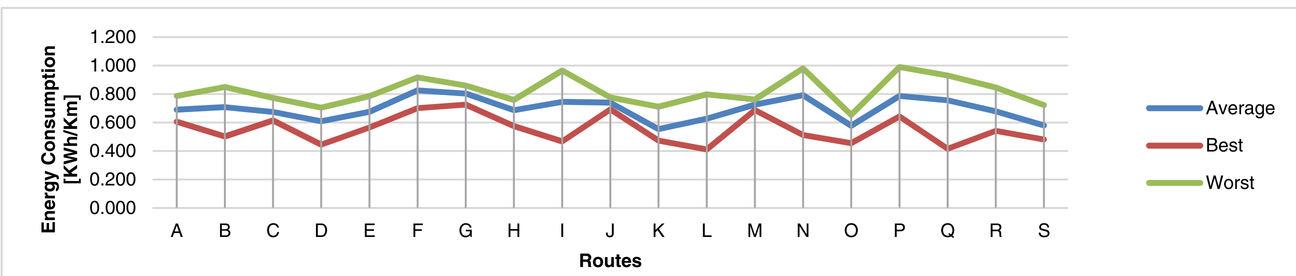

FIGURE 20. 365-days energy consumption over routes (around the clock).

E. ALTERNATIVE SIMULATIONS

This section explains the alternative simulation approaches and measured the efficiency of the proposed approach and simulation with other methods.

1) JAVA MODELING TOOL (JMT) SIMULATION MODEL

Figure 32 shows the JMT simulation model in comparison to the bus recharging model designed and simulated in figure 15. As shown in figure 32, a bus is having a pre-defined scheduler for charging and it goes through multiple recharging stations in a sequence after waiting in the queue. After the bus battery is recharged, it has to wait for scheduling for on-route travel. This wait is defined in the output queue. Thereafter a schedule puts a bus on the route and it completes its journey. All assumptions of this model are the same as of JaamSim simulator model defined earlier except that JMT tools have its processing and statistical method of implementing the logic.

FIGURE 21. 100-days energy consumption over routes during peak hours (peak-1, peak-2, and peak-3).

FIGURE 22. 365-days energy consumption over routes during normal hours (early morning, morning-2, afternoon and night).

FIGURE 23. 5-years energy consumption over routes (around the clock).

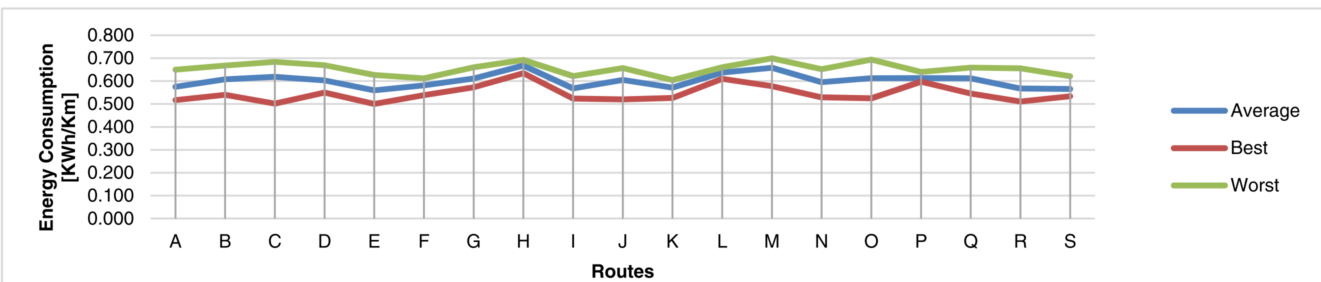

FIGURE 24. 5-years energy consumption over routes during normal hours (early morning, morning-2, afternoon and night).

2) CupCarbon SIMULATION MODEL

Figure 33 shows the CupCarbon simulation model for passengers and buses on-road traveling in the smart transportation system. This model is designed in comparison to the JaamSim model designed and simulated in figure 27. All assumptions are the same as those considered in JaamSim. However, statistical tools are not available in CupCabon. Here, sensors, routes, passengers and recharging stations and buses are only

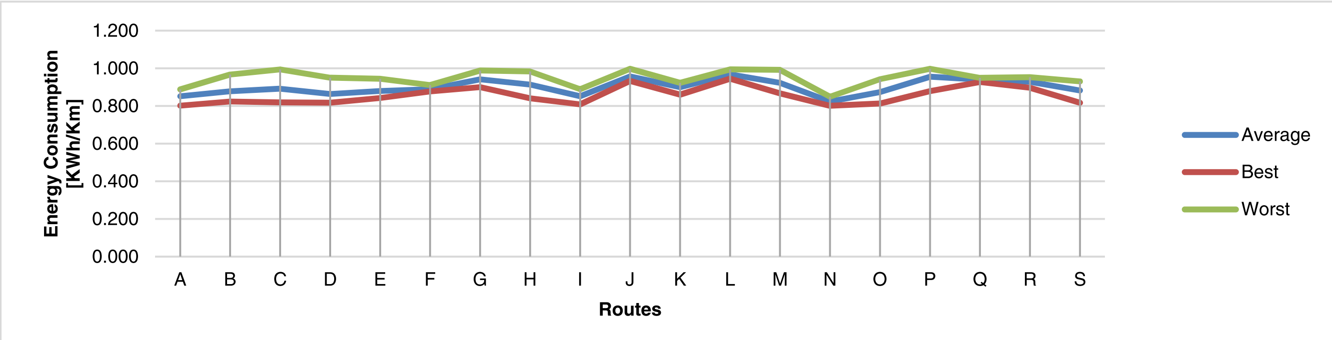

FIGURE 25. 5-years energy consumption over routes during peak hours (peak-1, peak-2, and peak-3).

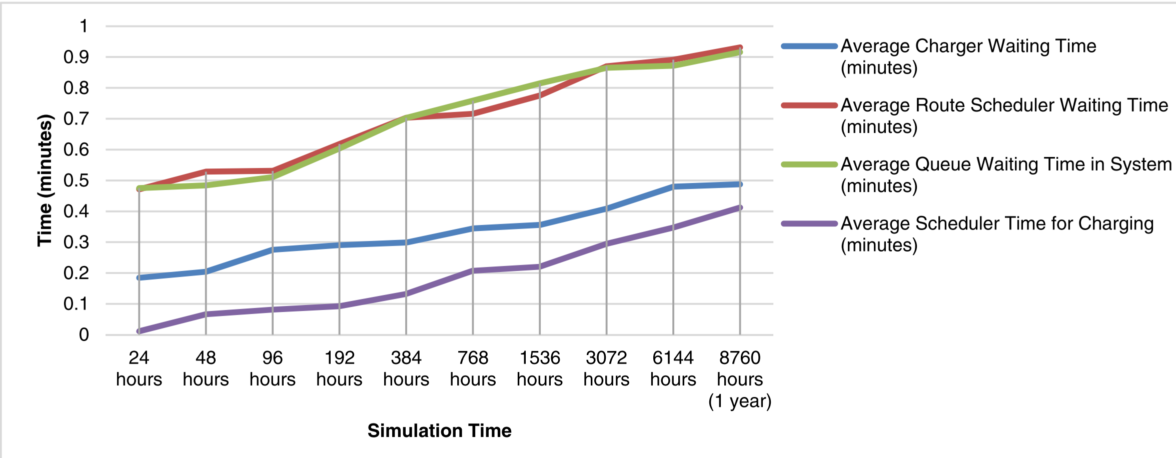

FIGURE 26. comparative analysis of variations in different timing parameters over the simulation time.

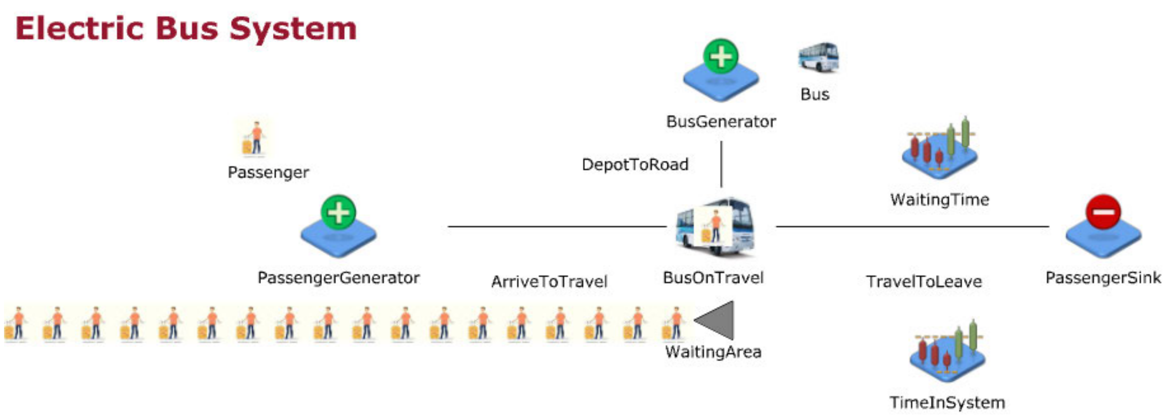

FIGURE 27. JaamSim model for passengers boarding electric bus in execution.

programmed over geographical maps collected from google maps. Dehradun's geographical map is collected from google maps, uploaded in CupCarbon simulator and programmed as per smart city project design [8].

3) COMPARATIVE RESULT ANALYSIS

Table 8 and 9 shows the statistical comparative analysis of results. The results are compared for the JaamSim simulation model with JMT and CupCarbon simulation results. Table 8 is the comparative analysis of the JaamSim model with JMT model over four parameters simulated for a 1-year simulation time. Results show a minimum of 0.02% (for average scheduler time for charging) and a maximum of 0.06% (for average charger waiting time and average queue waiting time in system) errors. Table 9 shows the JaamSim simulation model comparison with CupCarbon for passengers waiting

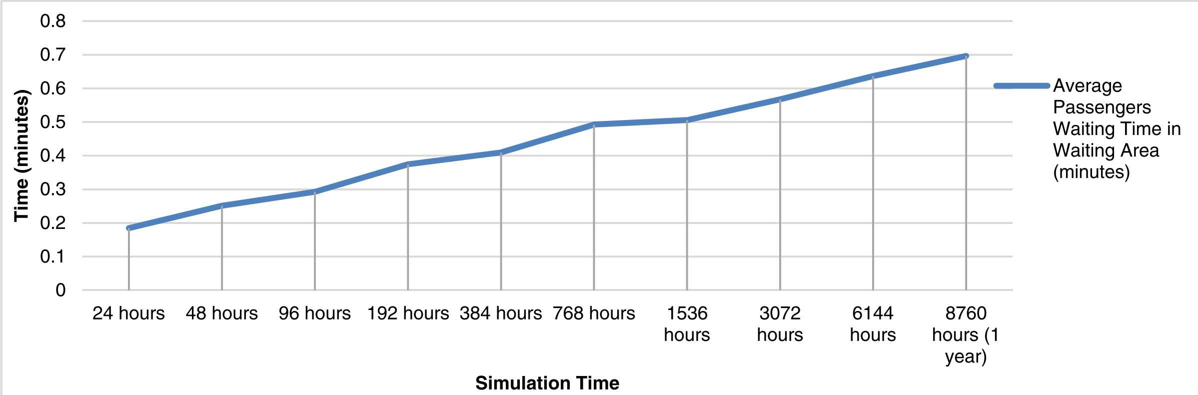

FIGURE 28. Comparative analysis of the average passenger's waiting time in the waiting area.

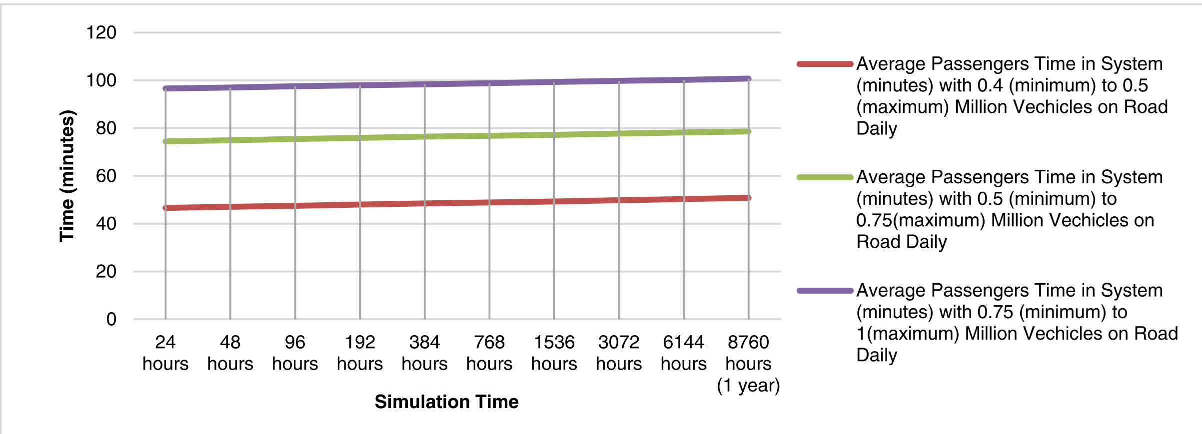

FIGURE 29. Comparative analysis of average passengers' total time in the system with variations in the number of on-road vehicles.

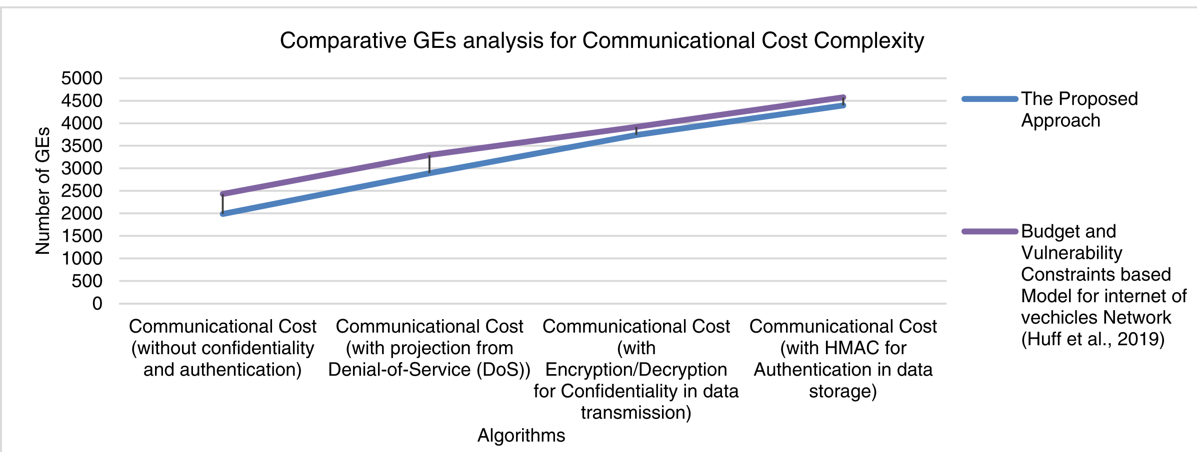

FIGURE 30. Comparative analysis of communicational costs with different security primitives.

time with variations in vehicles. This comparative analysis shows a minimum of −0.04% (for average passenger time in system (minutes) with 0.5 to 0.75 million vehicles on road daily) and a maximum of −0.01% (for average passenger

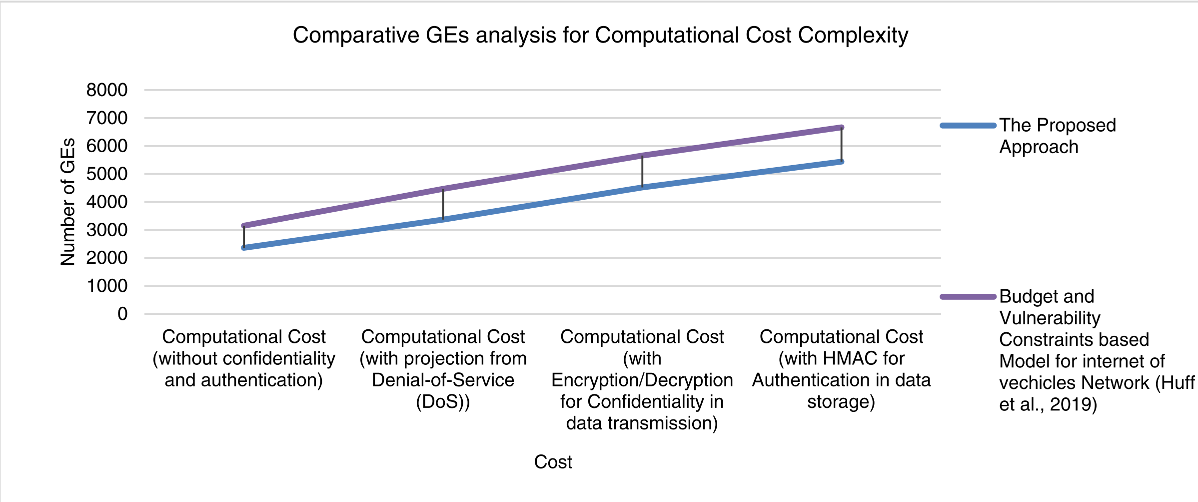

FIGURE 31. **Comparative analysis of computational costs with different security primitives.**

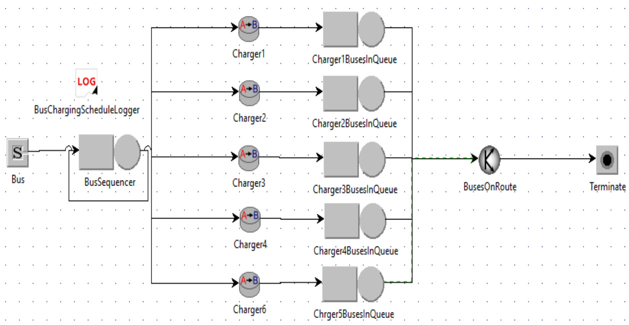

FIGURE 32. **JMT simulation model for bus charging in smart transportation system.**

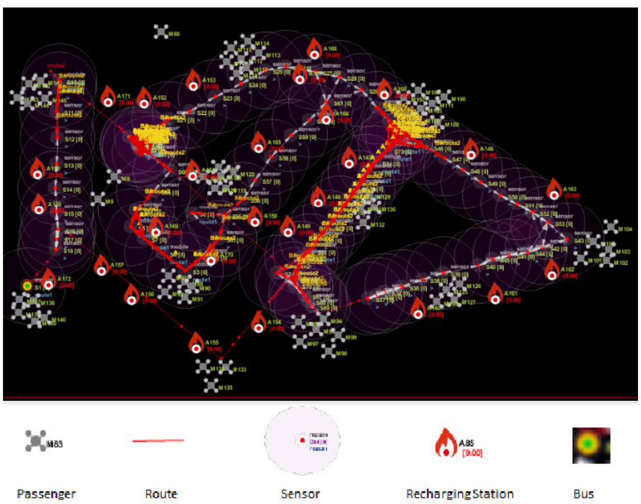

FIGURE 33. **CupCarbon simulation model for passengers and buses on-road travel in smart transportation system.**

TABLE 8. **JaamSim vs JMT comparative simulation analysis.**

Parameter (for 1-year)	JaamSim Model	JMT Model	Percentage of Error
Average Charger Waiting Time	0.93	0.87	0.06
Average Route Scheduler Waiting Time	0.91	0.88	0.03
Average Queue Waiting Time in System	0.49	0.46	0.06
Average Scheduler Time for Charging	0.41	0.40	0.02

Note: Table values are the average value of 5 executions.

TABLE 9. **JaamSim vs CupCarbon comparative simulation analysis.**

Parameter (for 1-year)	JaamSim Model	CupCarbon Model	Percentage of Error
Average Passengers Time in System (minutes) with 0.4 to 0.5 Million Vehicles on Road Daily	48.7	49.1	-0.01
Average Passengers Time in System (minutes) with 0.5 to 0.75 Million Vehicles on Road Daily	79.2	82.4	-0.04
Average Passengers Time in System (minutes) with 0.75 to 0.1 Million Vehicles on Road Daily	102.1	104.6	-0.02

Note: Table values are the average value of 5 executions.

time in system (minutes) with 0.4 to 0.5 million vehicles on road daily). These differences in results may be due to different internal working and statistical model applications in simulations.

VI. CONCLUSION

In this work, a simulation-optimization approach and Industry 4.0 is applied for modeling, analyzing and evaluating the feasibility of an electric-powered bus system in Dehradun smart city's public transportation system. The proposed simulation-optimization based public transportation system is composed of multiple routes with 100 stops served by 15 buses as per the pre-defined schedule. Placement of system entities has been optimized by using a local-global multi-objective simulation-optimization algorithm that considers multiple dependent and independent variables for improving overall system performance. The results show that the proposed approach requires GEs lesser than the existing approach with the integration of security primitives as well. Both, communication and computational cost measurements show that the proposed approach is lightweight in implementation and suited for resource-constrained devices. Simulation results show that the average passenger's waiting time varies between 0.2 minutes (for 24 hours) and 0.7 minutes (for 1 year). This waiting time increases with an increase in traffic over roads. In regular traffic conditions, an average passenger's travel time varies between 41.6 minutes (for 24 hours) to 45.5 minutes (for 1 year). In the future, integration of more security primitives (such as non-repudiation, integrity, authentication etc.) is planned. Further, these primitives will be integrated with taking information stages (processing, storage, and transmission) into consideration. A quantitative measurement model specifying standards is required to consider the whole system under the full-proof category. Simulated-annealing is an approach to solve bound-constrained optimization from the historical available data and experiences. However, an enhancement to the simulated-annealing approach is required to identify zero-knowledge constrained functions.

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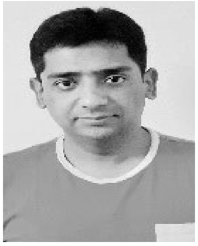

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