

Research Article

Context-Aware Services Using MANETs for Long-Distance Vehicular Systems: A Cognitive Agent-Based Model

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Long-distance transportation systems play an important role in economic growth. Yet, these systems are incurred with multifaceted delays and cost problems. The major incites affecting transportation systems are congestion, breakdowns, emergencies, and inclement weather. Scarcity of information about the environment also exacerbates travel problems. It is essential to employ monitoring and guidance that aid in making timely decisions through premediated information. This work aims to provide a flexible model for the long-distance transport system. The model is based on problems faced in long-distance transportation. Moreover, we examine the possible use of emerging Information and Communication Technologies (ICTs) for better transportation. The system dynamics study the problem at hand through cognitive agent-based modelling (ABM) concepts. The integrated model lays the rules to abate traffic delays. In this model, the distance travelled by vehicles is divided into sections using checkpoints. Every section is composed of different agents such as medical units, police stations, workshops, and petrol pumps. The vehicle shifts connection over the mobile ad hoc network (MANET) when enters or leaves a section. We used NetLogo for simulation of the model. A monitoring and guidance system is tested, and obtained results are analyzed by addressing problems causing delays. The guidance system helps vehicles to take optimal decisions for the time, congestion, and rests. The model can be used to improve decision-making for vehicles through premediated decisions. The proposed model can help to improve the efficiency of the transportation systems by reducing travel time.

1. Introduction

Transportation models are signified as a cardinal economic indicator for economic growth and encompass enormous investments in the transportation system [1–3]. The congestion problem in long-distance transport caused 1.2 billion hours of delay in the USA reported through the NHS [4]. Travel time is one of decisive constraints in the selection of a transport model [5]. Transport problems are multifaceted comprising of constraints such as travel time, fleet compatibility, and environmental effects [6]. Delays in

transportation encumber the economic value of logistical systems, thus requiring expedient models [7]. Theft and breakage risks decrease the performance of a transportation system through inhibited areas. It is essential to ameliorate transportation systems by detection and aversion of such risks [8]. Road conditions and rest time also evince the transport system's efficacy. Expedient planning coupled with retroactive knowledge can dwindle the probability of delays [2]. Modern logistical technologies for efficacy are imperative in the transport process [9]. The emerging Information and Communication Technologies

such as the Internet of Things, smart-contract, wireless sensor networks, knowledge engineering, and deep learning are aimed at connection and smartness of everything.

Research on smart and autonomous vehicles have significantly gained popularity. Efficient processing of information helps taking timely and correct decisions. Long-distance vehicles are also focused to adopt such technologies for enhancing efficiency and facilitate the users. Transportation systems are manifold of complex macrocosms (entities and processes) involving the employment of forecasting and analyzing traffic flows. Transportation modelling accosts to study and evaluate transportation system dynamics. The advent of Information and Communication Technologies with transportation systems aids in real-time information exchange and decision-making. Therefore, a sustainable transport system consolidated with modern technologies is cardinal, thus providing improved substitutes to transport entities to avoid unwanted circumstances. Cognitive agent-based modelling uses decision-making agents. The rationale decisions based on travel time and traffic conditions entail efficient transport models.

This work is an effort to identify the core challenges in monitoring long-distance transportation through ICT for effective transportation systems. The research implications are wide-ranging and especially to China-Pakistan Economic Corridor (CPEC). According to the official website of China-Pakistan Economic Corridor (CPEC) <http://c-pecc.com/en/about/about-47.html>, a road leveraging about 3000 KM from Kashgar is located in China to Gwadar Port of Pakistan as shown in Figure 1. CPEC, apart from roads, includes railway and projects of Information and Communication Technologies as shown in Figure 2. China will use CPEC roads to trade with the rest of the world through the Indian Ocean. CPEC passes through different types of landscapes. There are several places on this route where the drive is difficult, and the facilities are very minimal. Karakorum highway is a part of this route is considered as one of the wonders of the world. Therefore, in such case, proper ICT-based facilitation is important for different stakeholders including drivers and crew staff. This research aims to identify and model the conventional problems faced by long-distance transportation systems during the journey by answering the following research questions:

How travel delays and congestion contribute towards inefficient transportation?

How monitoring and guidance through ICT aid to simplify decisions in long-distance transportation?

How can we model and simulate context-aware long-distance transport systems for the purpose of understanding and analysis?

The remainder of this paper is organized as follows: in Section 2, we briefly analyze the literature review. After literature review, Section-3 illustrates the agent-based model and relevant concepts. In Section-4 we discussed the

simulation and results. Section-5 discusses the issues and findings. We conclude our paper in Section 6.

2. Literature Review

Transportation system entities are pluralistic and can be represented as agents [10]. The agent-based modelling (ABM) approaches are used in numerous studies [11–13] involving complex and decentralized systems [14, 15]. Agent-based modelling captures communication and interaction between agents finding solutions to issues involved in multiagent systems using a simulated environment [16–18]. ABM amalgamated with other forms of transport modelling helps to capture entity level details, complex decision-making, and visualization of the behaviour of drivers and other agents [19, 20]. The ABM has been effective in modelling the behaviour and interaction of the vehicle with the passengers, estimating passenger interaction with metros, and estimating exposures to air pollutions from transportation [21–23].

Transport models allow to formulate travel plans and trends are changing rapidly [24, 25]. Several studies propose and evaluate the use of integrated systems incorporated with ICT [11, 25–28]. However, most of these do not deal with the transport problems faced at the road due to road conditions, rest times, and emergency situations. Additionally, transportation data are less available in disturbance areas [29]. Therefore, better data availability for each agent helps to make optimal decisions [11, 30]. Thus, tracking and monitoring can identify the time to reach destinations and other pertinent parameters (speed, condition, and location) during the trip in long-distance vehicles [26]. Transportation systems can typically be modelled with several available software applications and can be tested in simulated environments [27]. Another study [31] involving a prototype to capture truck patterns for average working day examined the transport entities during transportation. However, the work is limited to cater choice behaviour of respective agents and time choice. Another study presents a multiscale agent-based simulation representing agent behaviour and interactions [32]. The traffic situation has a direct effect on travel time. Consequently, congestion play a significant role in increasing travel time [33].

Agent-based modelling is recognized as an effective approach for modelling complex problems in domain ICT systems through the application of cognitive agent-based computing [34, 35]. The agent-based modelling approach can be used to model the system dynamics of a transportation system. It is evident through the literature that several scientific studies used ICT in freight transportation and most of these do not involve the problems faced by vehicles on the road [27] which can be alleviated. On-road problems and travel time parameters are monotonous with slight vicissitude in the way of being addressed in conducted studies. The work is compared on four constituents: weather conditions (WC), emergency stops (EMR), congestions



FIGURE 1: Road map of CPEC (<http://cpec.gov.pk/maps>).

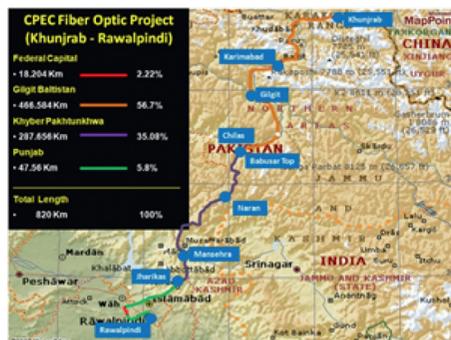


FIGURE 2: ICT project of fiber optic (<http://cpec.gov.pk/maps>).

(Cong), and rest time (Rest). Some approaches model freight transport to cater the weather conditions and road transport externality to addresses involved factors without incorporating the rest time and congestions [36, 37]. The model proposed in this study also assays these factors with integration with the ICT system in place.

3. Model for MANET Enabled Long-Distance Transport

The transport system is a compound microcosm of transport entities. ABM allows autonomous agents with behaviour and attributes which may interact with one another. We can also model the relationships between the agents, and the environment may also be considered [38]. The ABM approach permits to capture vehicle interactions with the other (connected) agents and their behaviour. ABM is suitable for continuous and ad hoc systems. The proposed model investigates the travel time and several other parameters in long-distance transport. The process of monitoring vehicle using GPS is continuous time whereas different working boundaries of supporting agents on roads create multiple MANETs. We are using decision-making agents which may better be modelled by cognitive agent-based models. Hence, our model is a cognitive exploratory agent based. A vehicle travels to deliver freight to an elongated destination with sporadic breaks in long-distance transport. As the vehicle moves through, it interacts with fuel stations for fuel fill-ups. Drivers take explicit rest intermittently at rest areas. The vehicle may also interact with medical or police stations in case of any medical or lawful emergency. The breakage in the vehicle also requires workshop involvement. During the travel, communication is carried out through shipment managers. Therefore, our proposed model accommodates the stated entities and provides a mechanism to have connected entities using ICT. The interrelated agents interact with each other through a communication channel. Figure 3 depicts an integrated interaction model of transport agents. An agent-based model must be integrated with the ICT model to constitute the guidance and monitoring system for transport entities during travel.

The model is a composite of two tiers: the agent tier, which encompasses vehicle agents, is modelled through the ABM approach and the service tier, which represents a service provision model. The primary entities are the trucks, and secondary entities are supporting agents (police vans (PV), medical vans (MV), mobile workshops (MW), rest areas (RA), and fuel stations (FS)). The vehicle position is tracked through geopositioning devices installed on the vehicle itself. The agent tier also captures the interaction of vehicle agents with each other agents. The service tier provides a service provision mechanism through the exchange of information using the web services model. The services can be provided by diverse service providers (WS1, WS2...WSn) through a communication channel. These supporting services are helpful to discover about the weather conditions, road situations, rest, and fuel stations as well as the communication with service vans/stations. The agent tier and the service tier synchronously work in parallel to record

the agent interaction and required essential information. Both tiers yield the resultant information which is coupled with the current situation of the environment and vehicle.

Figure 4 elaborates the customary transitions for primary vehicles of the proposed model. The “continue movement” state delineates the vehicle moving state. Thus, a vehicle can move into this state from any other state and vice versa. The states after the “continue movement” state can occur sporadically. The activity model prescribes rules that the vehicle may choose to rest on congested checkpoints provided the threshold time remains within the limits set by participating agents. The vehicle malfunctions and emergencies result in a mobile workshop and medical van models, respectively. The selection of model subjects to the nature of the incident. The details of submodels are described in the next sections. The vehicle may adapt speeds arbitrarily and due to road and weather conditions. The vehicle terminates its journey on reaching the destination. The model captures the emergent properties of vehicles during travel and suggests the appropriate actions through the help of ICT. Therefore, the provision of tracking and monitoring services can result in attenuated travel delays. The checkpoints measure the congestion level and track the progress of the vehicle by monitoring travel time. Vehicle gadgets also transmit location, and web services can be used to monitor, track, and guide vehicles during their trips for synchronized actions. ICTs (web services) help to recommend optimal decisions to the cognitive agents in a timely manner. A cognitive agent is a type of agent which can take decisions.

Evidently, agents in the model are mobile and are interconnected through ICT. A mobile agent is a type of agent which owns the property of mobility. Checkpoints are immobile and static agents in the system. Global Positioning System is a technology which enables the use of location-based services. Similarly, road conditions, weather conditions, and checkpoint communications are done by the smart devices. Several telecommunication technologies such as 3G, 4G, or 5G can help in real-time and direct communication between agents. However, in the case of inaccessible long-range communication channels, location services can be used at checkpoints. The proposed model is flexible to integrate new service provisions through interoperability.

The proposed mechanism for communication between a service vehicle (police, medical, or workshop) is depicted in Figure 5. The support services are managed through a queuing system implemented at the macrolevel between the two checkpoints. The support vehicles process the request queue and provide service to a newly received request in the case of availability. The request may be marked as waiting state of it which can be forwarded to another supporting agent. The provision of service can be supplied on the road or on the station depending upon the severity of the task at hand.

3.1. Travel Time Emergence. The model’s cardinal property is total travel time. Total travel time is defined as the time taken from origin to destination. The primary notations and

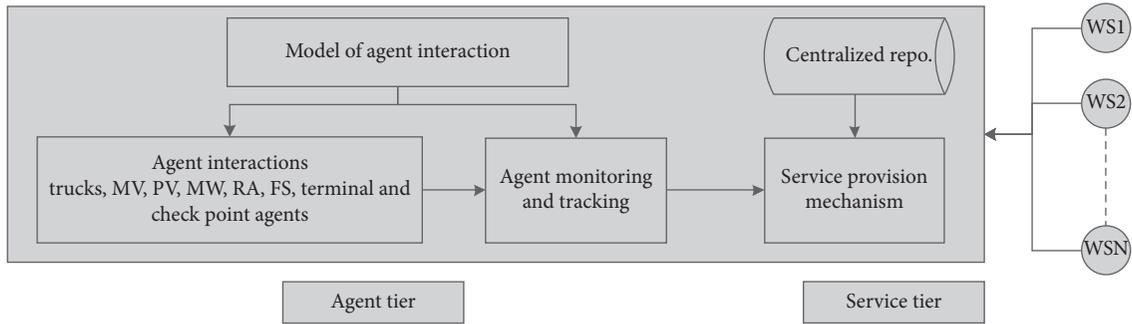


FIGURE 3: The integrated interaction model of agents for the proposed approach.

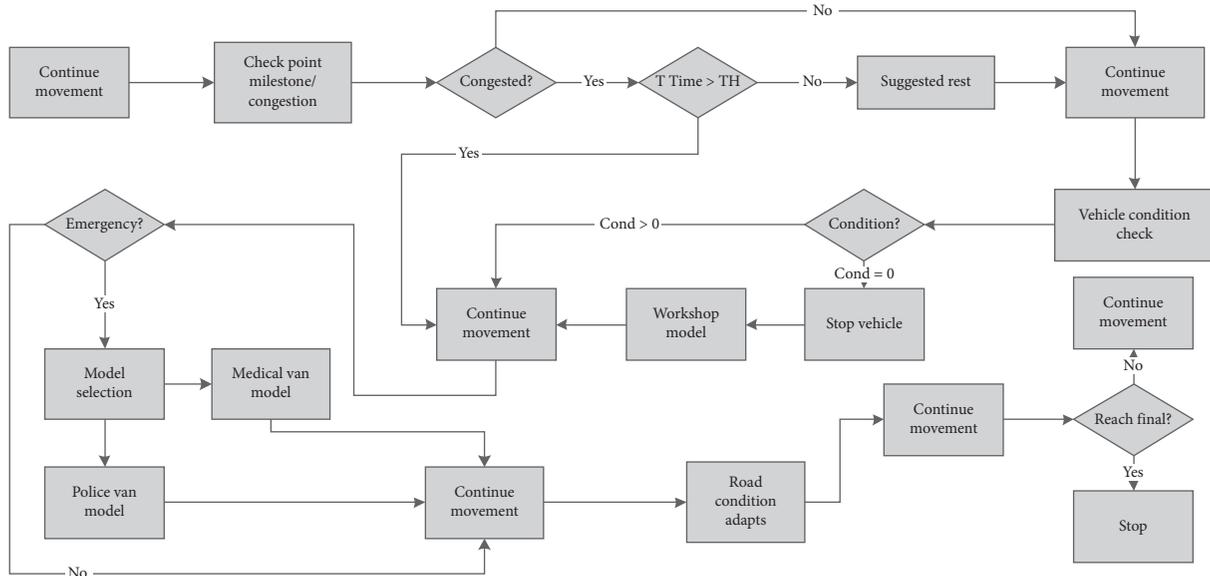


FIGURE 4: Stochastic activity diagram for the combined model.

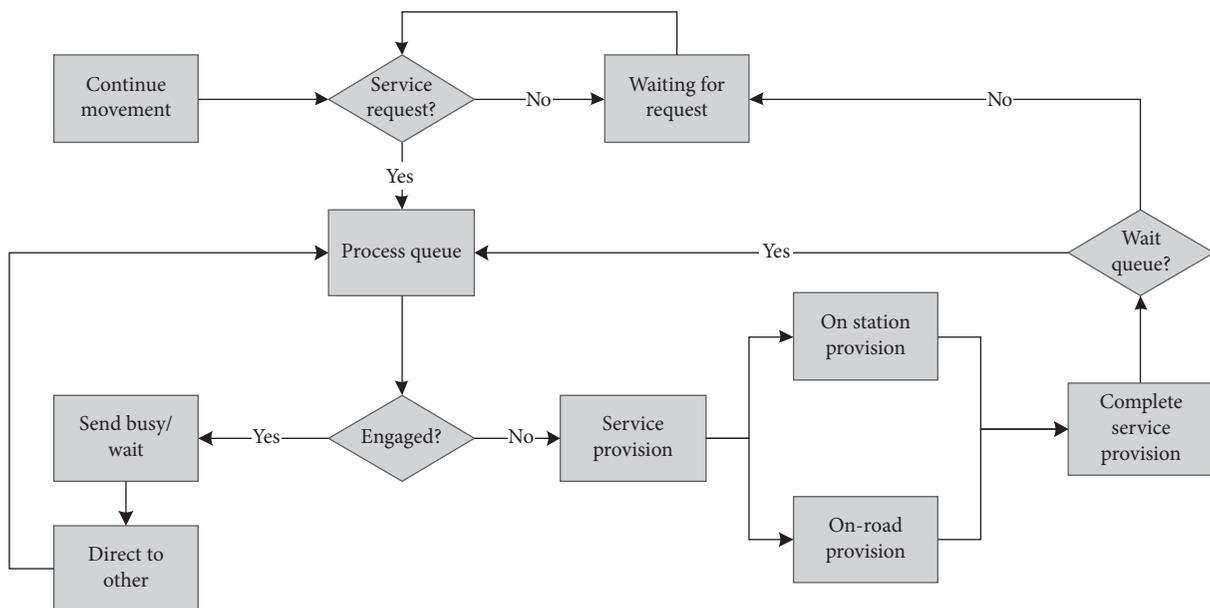


FIGURE 5: Stochastic activity diagram medical/police/workshop vans with the vehicles.

variables used to represent the system are depicted in Table 1:

$$\text{Travel Time } [v] = \sum_{\text{cps}=0}^C \Delta T[\text{cps}, \text{cps} - 1], \quad (1)$$

where the travel time is calculated as the sum of time between each checkpoint up to C-number of checkpoints. The checkpoints restraint the travel time duration between two checkpoints, which is defined as

$$\Delta T = \text{TCP}[\text{cps}] - \text{TCP}[\text{cps} - 1]. \quad (2)$$

TCP [cps] and TCP [cps-1] are the time observed at the current and anterior checkpoints. If a vehicle is behind the schedule, the route plan is updated for a vehicle with shortened rest periods and increasing optimal speeds. Total time is the sum of travel time, rest time, and wasted time (time spent at repairs or emergency cases):

$$\text{Total Time}[v] = \text{Travel Time}[v] + \text{Rest Time}[v] + \text{RPMT}[v]. \quad (3)$$

3.2. Congestions. The traffic congestion level at each checkpoint point is a consequential indicator for efficient transportation. Congestion increase results in increased travel time. Congestion capacity is defined at checkpoints:

$$\text{Cong}[\text{cps}] = (\text{Cap}[\text{cps}, \text{cps} - 1]) - \text{VC}[\text{cps}, \text{cps} - 1], \quad (4)$$

where Cong[cps] is a level of congestion at a checkpoint. The vehicles are guided to continue movement or rest depending upon the congestion level for optimal travel time. (Cap[cps, cps - 1]) is defined as the capacity between consecutive checkpoints where the VC[cps, cps - 1] is the actual volume between two checkpoints in “continue movement” state.

The agents interact with each other to specify their current state to update the global environmental situation. The ratio is a primary measure to find congestion and is defined as

$$\text{Ratio}(\text{Cong}[\text{cps}]) = \frac{\text{VC}[\text{cps}, \text{cps} - 1]}{(\text{Cap}[\text{cps}, \text{cps} - 1])}. \quad (5)$$

A checkpoint is marked congested if the ratio approaches a threshold. Decisions for a vehicle to enter a congested area or wait for congestion to end is primarily based on the travel time. The best (B) selection from the movement or rest is carried out as

$$\text{Movement} = B(LW[\text{TravelTime}], (\text{Rest}[v, \text{cps}])), \quad (6)$$

$$\text{Rest}[v, \text{cps}] = (\text{Cong}[\text{cps}] \wedge ((\text{Total Time}[v] < \text{TCP}[v, \text{cps}]) \vee (\text{Rest Time}[v] < \text{th}))), \quad (7)$$

where LW[TravelTime] is a weighted value for total travel time. Weighted value is an acceptable delay in travel time

with respect to the probability to choose rest. Cong[cps] refers whether a checkpoint is congested or not. The Rest [v, cps] is the rest choice based on congestion, total travel time at current checkpoint, and rest time threshold. B defines the best criteria between the two. The movement decision is made after evaluating the nearby situation. Thus, agents' trucks with satisfied schedule are more persistently recommended for the rest to enervate congestion levels. Consequently, the trucks are allowed behind the schedule to pass through. Rest choice relies on the aggregation of travel time and congestion levels. However, the vehicle cannot rest for longer than the threshold limit. If the vehicle rest time exceeds the defined level, the vehicle continues the movement. Similarly, a vehicle continues its movement if the rest time increases and travel time approaches the schedule. The checkpoint is congested if congestion ratio exceeds the specified threshold. Vehicles adjust as per congestion levels, resulting in accrual or reduction in speeds. The decision for optimal speed is based on the time of travel:

$$\text{VS}[v] = \text{VSmax}[v] \text{ if } \text{Total Time}[v] > \text{TCP}[v, \text{cps}] \\ \text{VSe}[v] \text{ if } \text{Total Time}[v] < \text{TCP}[v, \text{cps}]. \quad (8)$$

3.3. Agents and Sensor Communication. Vehicle agents with on-board units communicate location, sense, and calculate the time to reach next checkpoint. Help services (traffic, weather, and road conditions) accommodate finding better observations. Sensing and transferring information can be described as below for nearest and best possible sensor selection criteria. Let S be a sensor, then the super choice (Sup[s] is the use of available sensors for direction communication) in the selection of sensor, nearest criteria choice (Nr[s] is the use of available sensors for communication through checkpoints), and the best choice will be aggregation (Aggr.) of both:

$$S[s] = \text{Sup}[s_1, s_2, s_3, \dots, s_n], \quad (9)$$

$$N[s] = \text{Nr}[s_1, s_2, s_3, \dots, s_n], \quad (10)$$

$$B[s] = \text{Aggr.}[Bs \wedge Ns]. \quad (11)$$

The workshops, police vehicles, or medical vans will serve the requests within specified checkpoint as

$$\text{request}(\text{truck}[v], \text{cps}(\text{truck}[v])) \\ \longrightarrow \text{Service}(\text{cps}(\text{truck}[v])), \quad (12)$$

$$\text{State}[v] = \text{Breakage} \text{ if } \text{cond}[v] \leq 0, \quad (13)$$

$$\text{RPMT}[v] + = \text{Repair Time}[v]. \quad (14)$$

The vehicle must transmit location with workshops, police stations, service areas, or medical help in case of vehicle damage, emergency, or threat. Interactions are done through information exchange by sensors or web services using wide-area communications such as 3 G/4G. However, these services work indigenously and over short distances.

TABLE 1: Notations and variables used for the representation of transport systems.

Entities	States	Definitions
	Vehicle index	$v=1, 2, 3, \dots, N$
	Checkpoint index	$cps=1, 2, 3, \dots, C$
	Time target at the checkpoint for vehicle	TCP [v, cps]
	Total travel time	TotalTime[v]
	Travel time (on-road)	TravelTime[v]
Variables	Time spent at rest	RestTime[v]
	Wasted time (no travel)	RPMT[v]
	Current speed of vehicle	VS[v]
	Minimum speed	Vsmin[v]
	Maximum speed	Vsmax[v]
	Efficient speed	VSe[v]
	State	State[v]
Stochastic variables	Time window	$[\Delta T, \text{TotalTime}]$
	Condition of vehicle	Cond[v]
	Congested cps	Cong[cps]
	Rest choice	Rest [v, cps]

Apparently, the short-distance services will contextualize to localized versions with set checkpoint areas.

3.4. Supporting Services. The model integrates with short-distance supporting services such as emergency, repairs, and legal. The short-distance services congregate with long-distance transportation through employments of checkpoints. The communication with these services is location-based. The service providers must be recognized within the system. The area covered by each instance of the agent is predefined, and communication between the vehicle and emergency support vehicles is within that area. Agents, to request for services, must be able to send their locations to central repositories or other agents by means of a GPS/GSM device. A smart device containing a tag/token for unique identification of the truck must also be included. At each checkpoint truck, tags are read, and the information is exchanged to guide trucks with respect to travel times, efficient speed, etc.

4. Simulation and Results

The model is simulated using NetLogo platform. NetLogo has been extensively used to model multiagent systems in countless studies and well-known books on agent-based modelling [39, 40]. It is a highly flexible and customizable tool for modelling diverse applications in a multiagent environment. Our model necessitates the congregation of various agents with each other environment-wide and indigenously between the checkpoints. Also, we have heterogeneous agents such as workshops and police. Hence, NetLogo provides the flexibility desired for the task. Agents with mutually implicit and explicit characteristics can be modelled to observe system dynamics and their interactions in NetLogo [41]. We have used exploratory agent-based modelling for the purpose of feasibility analysis [42].

4.1. Simulation Environment. The simulation space contains infrastructure such as various roads, checkpoints, and emergency service stations. For evaluations and simulation purposes, a single one-way road spreading across multiple checkpoints (stations) is mapped in the environment. The distribution of agents is established along with checkpoints. The long-distance vehicle travels across multiple checkpoints or throughout the road. However, the communication and situations of short distance (mobile vans and rest areas) are restricted between the checkpoints. The mobile and rest area agents share similar attributes along with their status of being in service or not. Weather conditions are implemented in three categories, e.g., normal, bad, and worse. Bad and worse weather conditions cause the vehicle to travel at lower speeds and more delays with a variable probability for each type of truck. Light trucks have lower levels of load and a higher level of speed and efficiency.

The state of some roads is altered arbitrarily to represent road deteriorations, weather, or congestion. Without any recovery measure for vehicles, the vehicle deteriorations increase travel time with an increased likelihood of breakdowns (mapped scale 1–5; where 1 is lowest and 5 means significant breakdowns). The scales are translated to apply probabilistic vehicle decay stochastically. Based on the scales, the proportionate number of vehicles deteriorates over the time. The other parameters are also measured at the same scale (1–5). With higher breakdown, more workshop encounters are required which is directly proportional to the increase in congestion depending upon the population size (vehicles) on road. Three types of trucks are modelled (heavy, medium, and light), and their required attributes such as speed, location, and time are represented. The traffic is simulated stochastically to reproduce difference scenarios with ranging congestion levels. The 200 units of time in simulation space are mapped as 1 hour with reference to the distance travelled by vehicles during the 200-unit timespan. The collected attributes of transportation systems are

simulated in the environment to observe travel time. The entities of the model including vehicles (trucks), police, medical, workshops, rest areas, and checkpoints are presented in Table 2.

4.2. Results. This section shows a comparative analysis of how using the guidance and monitoring system can improve long-distance transportation systems. Table 3 construes an increase in average travel time if there are bad weather conditions. It shows an increase in travel time in bad weather because heavy trucks already travel at lower speed and weather effects cause them to slow down at a higher level. The speed in Pakistan and its surroundings is measured in kilometers per hour (KM/H) as shown on the official website of Pakistan Road Safety (<http://www.roadsafetypakistan.pk/speed-limits>). For this reason, we have used the scale of distance in kilometers and the scale of time in hours. The data presented in Table 4 depict a subset of possible scenarios depicting enhanced proximity of vehicle breakages, need for emergency/supporting services, unplanned rests, and increased travel time due to bad weather and congestions during the travel. Factors affecting the overall travel time are presented in Table 4.

Travel time analysis of the collected data is delineated in Figure 6. The travel time can be reduced by automating the information and decisions of several factors. Tests are engendered through simulation of data sets ranging from different weather conditions, congestions, breakdown rates, police, and medical cases. The heavy trucks take more time to repair resulting in higher repair and travel time. With the weather condition interpolation and congestions along with other parameters, the travel time can vary. Test runs contain 15 percent of the area to be in bad weather conditions and 15 percent for the worst weather conditions for the test journey. Results indicate that weather problem combined with a high number of congestions and populations may increase travel time to a significant level for heavy trucks. The optimal decision between a selection of rest and movement in congestion is also controlled by several complex factors such as driver's predilection and available data to choose from foreseeable alternatives.

Mobile vehicles between checkpoints provide vehicles with assistance and recovery. If a vehicle encounters a problem, it may request a respective supporting agent. Figure 7 shows a comparative analysis of two different simulations with calibrated input trucks and final trucks reaching the destination with variable vehicle breakage rate (BR). Vehicle generates a repair signal when it enters the breakdown state. The signal is interpreted by available workshops within the checkpoint area. With the increase in breakdowns, the meantime to service those repairs will also increase. The test set is generated at 5000 ticks (25 hours) with different breakdown scales ranging from 1–5 (low to high). Meantime to repair remains constant over breakdown rate set at 1 and 3, respectively, whereas breakdown rate set at 5 produces more breakdowns. At 5, an increase in average repair-time happens due to unavailability of mobile workshops.

Analysis of two distinct medical cases and the average time to solve a medical case with respect to medical case rate (CR) over a population has been shown in Figure 8. Medical case generation rates (CR) are set from scale 1–3 (lower to higher). Test results simulated for approximately 3000 ticks (15 hours). A similar analysis of several police cases and the average time to solve a police case with respect to police case occurrence rate over a population is observed. The results show that having mobile vans and police vehicles in place and vehicle communicating directly to these in real-time reduces the time spent for emergencies. The model and the rules to interact with supporting agents are illustrated in Section 3.

The decision to enter congestion or take precautionary rest at a congested checkpoint is calculated on the accessibility of knowledge about an approaching road situation. If the approaching checkpoint is marked congested, then the vehicle may decide to rest depending upon its actual and expected arrival on that congestion governed by the rules presented in Section 3. Vehicles may have additional time to reach a target, i.e., reaching earlier than the deadline. For that purpose, additional time is added for the variability of decisions made by vehicles at each checkpoint. This additional time termed as late weight presented in the last section results in higher chances of taking rests. The following scenario presented in Figure 9 depicts four different test scenarios with varying parameters such as trucks, the total number of rests taken by truck population, distinct trucks taking rest choices, and the number of times the vehicle chose to enter in congestion due to high actual travel time, followed by several distinct vehicles chose to continue movement regardless of congestions.

Test results are generated at 2000 ticks (10 hours) and late weight set to 0-3-6-10, respectively. At weight set to zero, more trucks will enter in congestion due to high travel times and fewer trucks will enter in a rest state. With the higher late weight, the fewer trucks will enter in congestion due to available travel time and will look to avoid congestion by taking precautionary rests, thus resulting in reduced travel delays. The thresholds are applied arbitrarily to each test scenario. The number of vehicles entering congestion drops rapidly, and most vehicles enter in a rest state. While the late weight is set to 6 and 10 for the test 3 and 4, respectively, the number of trucks entering in rest states will increase and the number of trucks entering in congestion will decrease slightly. Results conclude that adding additional time for vehicles to travel through the simulation as late weight increases the chances of facing fewer congestions. Rest choices and congestion choices change oppositely with the increase of late factor.

The environment demonstrates congestion simulations. The case depicts the average delay time due to congestions and weather effects. Figure 10 illustrates the comparison through the evolution of congestion levels and problems occurred during the travel. The simulated environment measures the average delay occurred with and without the knowledge of road conditions and congestions ahead. In each run, vehicles are encountered with incidents intermittently. The effects of these problems can be minimized by

TABLE 2: Entities, state variables, and scales defined in the system.

Entities	States	Definitions
Global factors	Trucks/vehicle agents	N (input)
	Checkpoints	Fixed (14)
	Vans/rest areas per checkpoint	Fixed (1 for each type)
	Breakdowns in vehicles	Variable
	Congestion probability	Variable
Patches	Patch type/colour	Weather/congestion/road
	Width	401 units
	Height	41 units (4–5 lanes)
Trucks	Type	Shape (load, speed)
	Location	X-Cor. Y-Cor.
	Max-speed	0.8 units
	Min-speed	0.001 units (0 units)
	Load	Heavy, medium, light
	Travel time	T units
	Current checkpoint	0-N (checkpoints)
	Rest time	T units
	Time in breakdown/stoppages	T units
	Med. van pol. Vans mob. workshop checkpoints	Location
Max-speed		0.8 units
Min-speed		0.001 units (0 units)
Status		Y/N
Checkpoint		Y/N (radius)
Cases handled		1–N
Congestion time		T units

TABLE 3: Effects of bad weather conditions on travel time.

Type of truck	AVG distance (KM)	AVG speed (approx.)	AVG time (hours)	Bad weather AVG time (hours)
Light	1170	40 + Km/h	26	27.5
Medium	1137.5	30–40 Km/h	32.5	40.5
Heavy	1250	20–30 Km/h	50	67.5

TABLE 4: Effects of weather and congestion on breakage and unplanned requirements increasing travel time.

Type of truck	AVG distance	Weather	Congestion effects	Breakage likeliness	Medical required	Police required	Workshops required	Unplanned rests	Increased travel time likeliness
Light	1170	Normal	Low	1	1	1	1	1	1
Medium	1137.5	Bad	Medium	2	2	1	2	1	2
Heavy	1250	Worse	High	4	3	1	3	2	4

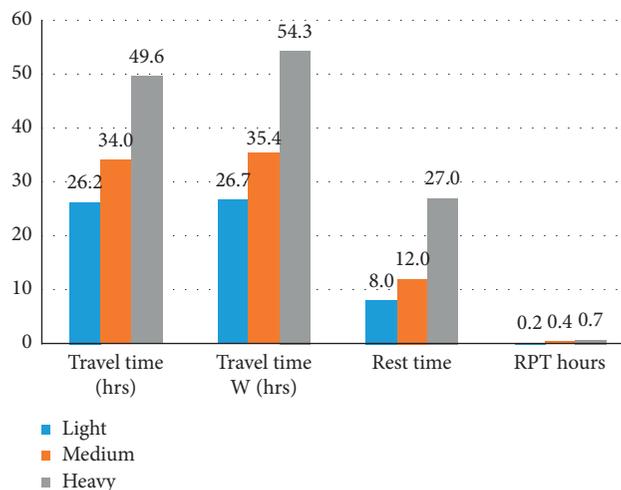


FIGURE 6: Travel times analysis for three truck categories (75 hours), with weather conditions applied and variable breakage rates affecting RPT (recovery time).

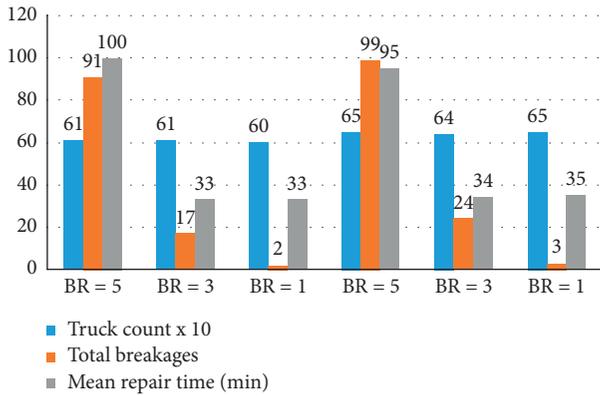


FIGURE 7: A comparative analysis of mean time to repair vehicles.

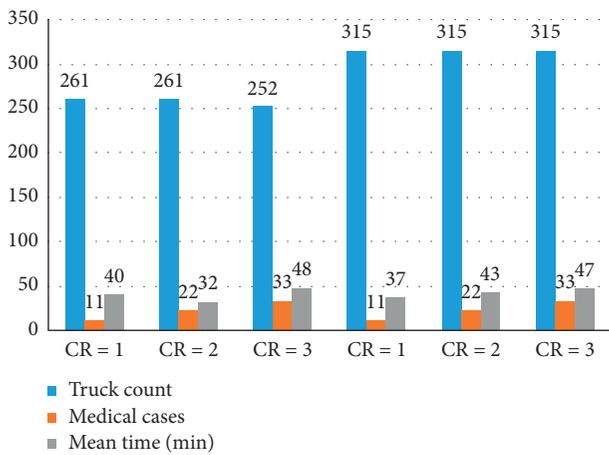


FIGURE 8: Comparative analysis of mean time to solve medical cases.

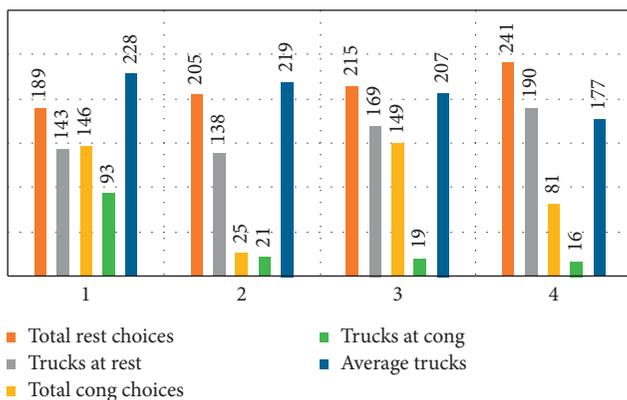


FIGURE 9: Vehicles choosing to rest at congestions due to extra late factor versus vehicles choosing to continue through congestion due to high travel time.

making decisions about whether to take rest and using the alternative time to travel. Vehicles with guided systems get familiar with the time-dependent travel condition, and better decisions are made to avoid extreme delays during peak hours. To find the impact of early congestion

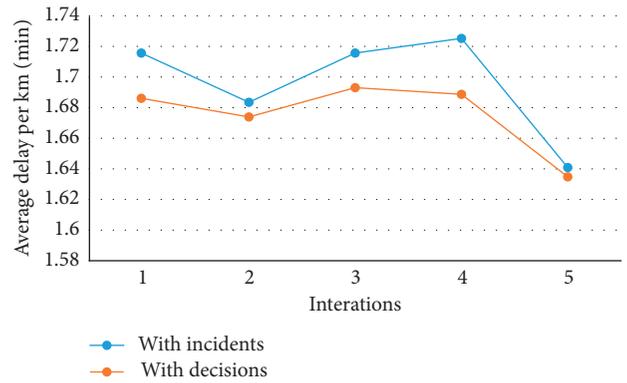


FIGURE 10: Measurement of congestion average delays with incidents and information system enabled.

information and the relationship between congestion problem and travel times, results are depicted in Figure 10. Selection of threshold is dependent on the capacity between two checkpoints with a decision to enter a congested area, or taking a rest choice is left for the vehicle as discussed in Section 3.

If the capacity increases from the defined threshold, the checkpoints are marked as congested and vehicles are provided with the information at the checkpoint. The comparison of delay in travel time is analyzed by setting the normal parameter first, then by increasing incidents, and then by placing a communication system proposed in the model. By incorporating the rules described in Section 3, the results show that average delay time can be decreased with incorporation of time-based checkpoints and the guidance system. Figure 11 depicts the improved performance by automating the decisions by the means of ICT Early Warning System (EWS). The baseline represents the optimum scenario without any incidents. However, baseline scenario in this case is a rare event as transportation systems are prone to experience unexpected circumstances. Therefore, the comparison illustrates the effect of placing a warning and guidance system can reduce the transportation delays.

5. Discussion

Travel time is a cardinal gauge to measure the efficacy of the transportation system. Breakdowns (e.g., vehicle depletion) and congestions are the major problems that derail the efficiency of transportation over a long distance. Weather conditions afflict the average speeds and enhance overall travel times. It incorporates the effects of weather and congestions on travel time. The proximity of vehicle breakages enhances the need for emergency/supporting services and unplanned rests and increases the travel time. Congestion also influences vehicle reliability and likely to result in higher travel times. Statistically, it is evident that the breakdown problem increases without measures defined to overcome this problem. However, with the introduction of mobile workshops to repair vehicles at the vehicle location, the overall efficiency of the system can be improved. The

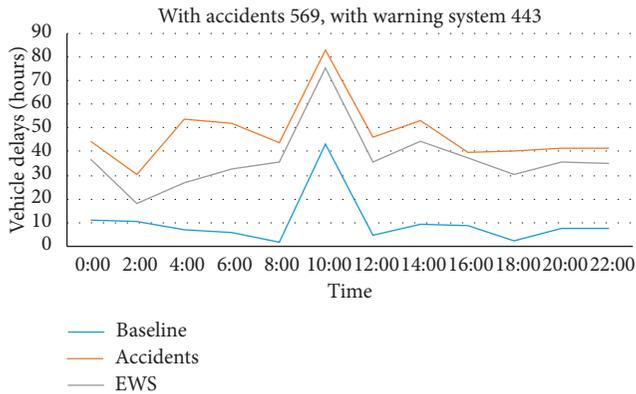


FIGURE 11: Normalized -22% decrease in delay in travel time due to the incorporation of a guidance system.

results are an indication that having a workshop in place and vehicle communicating directly to workshops in real-time reduces the time spent for searching for workshops for repair.

An ICT-equipped system along with vehicle services is essential for efficient transportation time. It has been depicted in the model that monitoring travel times and locations for on spot solution provision aid in improvements of the system. Primary agents (ICT-equipped trucks) must be aware of travel time constraints at all the time during the journey. Location and context-aware services enhance information availability and service provision. Analyzing the overall effect of using the integrated system including service basic information exchange, automatic tracking, and a guidance system results in improvements in the efficacy of transportation systems. Monitoring of transportation systems through real-time tracking and placement of checkpoints for the division of travel into sections increases optimal decision-making for vehicles during travel. The proposed model consequently will help to reduce congestions and ameliorate travel efficiency by properly managing the time spent on transportation interruptions. Simulations show a tradeoff between the agent's desire to take a rest against the needs of transportation systems to make an agent rest. Therefore, more comprehensive and robust mechanisms are required to accommodate and monitor rest choices. One possibility is using a reinforcement method to penalize agents in some form who act selfishly and ignore the rest recommendations during congestions.

6. Conclusion

The road and congestion problems in long-distance transportation result in delays having a chain of impacts. We used an agent-based modelling approach to estimate and measure the problems in transportation systems and proposed an integrated model. The model is based on the prospects of exchanging information in real-time using information and communication technologies. While moving across long distance, the vehicle connects to different MANETs. We simulated the model and tested retrospective conditions in NetLogo simulation environment. The integrated model

employing ICT features lays the rules to abate congestions, road problems, and rest delays. The results of the simulation model propose real-time communication for the incorporation of solutions to the overall delay problems including breakdowns, emergencies, congestions, and weather conditions. Results conclude that deciding optimal choice for congestion avoidance, travel time, or rest times is based on information provided at checkpoints and during transport. Using a guidance system, vehicles may be guided with better information, and depending upon the data collection for over a period for specific types of problems, better decisions can be provided for the system. However, the communication mechanism for diverse vehicles, sensors, and supporting agents is yet to be formulated. The limitation of this work also includes the interoperability of supporting agents with the vehicle (long distance).

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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