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Service-Level Agreement—Energy Cooperative Quickest Ambulance Routing for Critical Healthcare Services

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Abstract

In this study, the problem of critical ambulance routing scheme, which is a significant variant of the quickest path problem (QPP), was investigated. The proposed QPP incorporates additional factors, such as service-level agreement (SLA) and energy cooperation, to compute the SLA-energy cooperative quickest route (SEQR) for a real-time critical healthcare service vehicle (e.g., ambulance). The continuity of critical healthcare services depends on the performance of the transport system. Therefore, in this research, SLA and energy were proposed as important measures for quantifying the performance. The developed algorithm (SEQR) evaluates the SLA-energy cooperative quickest ambulance route according to the user's service requirements. The SEQR algorithm was tested with various transport networks. The SLAs and energy variation were quantified through the mean candidate *s*–*t* qualifying service set (QSS) routes for the service, average hop count, and average energy efficiency.

Keywords Critical healthcare services · Smart vehicles · Healthcare · Quickest route · SLA-Energy cooperation

1 Introduction

The transport system is the lifeline of a nation. Without sufficient transport support, aspects such as the economy, business, and the standard of living are affected. Therefore, transport planners/researchers put in considerable efforts for the development of a dependable transport network [1]. A transport network includes road networks, airlines networks, freight networks, railway networks, and all types of flow networks, such as water/power/gas supply networks and computer communication networks [2]. The transportation system has played an important role in making the human life more convenient through smart approaches for designing and developing infrastructure, such as driver assistantship, safe route discovery, traffic management, reliable routing, pre-computation of the optimal route, and quickest route problem [3,4]. These applications become proficient when different characteristics of network infrastructure, such as the capacity of network parts, energy, transportation risk, and service comfort, are included in planning and design [5,6]. Currently, transport systems enable the growth of businesses through massive smart approaches [7]. This feature can be easily observed in various sectors, such as health care, finance, stock exchange, production, and sale. The growth of a business is affected by numerous parameters, such as the minimum time consumption, minimum fuel consumption, and service-level agreements (SLA) satisfaction [8]. Hence, in this study, the aforementioned parameters have been analyzed.

Initially, most of the transport systems existed without depending on technology. Therefore, users of the transport system had to use their services without quantifying any service boundaries. However, as transport systems evolved through technology, users began to have control over the service delivered, and the quantification of user service satisfaction became an area of academic interest. Therefore, SLAs were imposed on transport systems [9]. SLAs refer to the mutual agreement points in writing between service providers and users. SLAs can be include numerous terms, such as the service time, mean time to failure (MTTF), up time, mean time to repair, and down time. If these terms are violated, a penalty is drawn for the services. By applying SLAs, the terms and relations between service providers

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and users become powerful. Therefore, the transport system becomes more effective, which leads to its overall growth. Numerous services and applications have begun to evolve SLAs for transport systems [10]. In this study, the other main objective is to incorporate SLAs with transport systems that support healthcare services (i.e., ambulance routing). When transport systems were designed fossil energy resources were considered cheap and unlimited. However, issues such as the energy cost and related environmental concern were not considered. The increasing demand of fossil energy resources has further deteriorated the environmental conditions [11]. Therefore, transportation authorities must prevent the use of these resources. Therefore, fossil energy resources must be replaced with the green energy resources [12]. Currently, a battery-operated electric vehicle is considered as a user of green energy with a limited capacity [13].

Over the previous decade, the use of healthcare services has increased due to the improvement in transport systems caused by technological support. Transport systems have extended healthcare services through door-to-door (DTD) and hospital-to-home (HTH) services [14]. According to the literature, in 2011, approximately 4.7 million patients received HTH services in the USA and 12,200 HTH service providers registered to provide services. In 2012, these numbers increased considerably, which indicates the necessity of HTH services. HTH services are classified as a profitable market. Due to the competitive market, HTH services must be improved over the traditional method [15]. Both DTD and HTH services are useful in various situations. These services should be made available to patients in between the hospital and home. In all these scenarios, an ambulance plays an important role in DTD and HTH services. The road route used by the ambulance should require the minimum time.

HTH services may incorporate various additional applications, such as home care, mobile care, nurse scheduling, and equipment surveillance healthcare. Considerable literature supports the importance of HTH services, where optimal service planning involves complex and challenging problems. Recently, an overview of the management problems and various applications of healthcare services have been provided in papers, in which the routing decision, staff assignment, and scheduling of services have been studied by various authors [16–19]. Most HTH services are time-sensitive. Hence, an excessive delay in obtaining HTH services can result in the loss of life [20]. In the execution of HTH services, the available road network has considerable uncertainties, which increases the complexity of the vehicle routing problem [21]. Moreover, the energy consumption during these services is an important issue, where the battery capacity of a vehicle is considered as a measure of the optimum scheduling. SLAs and energy constraints are important for ambulance routing from the viewpoints of criticality and continuity [22,23].

Considerable literature is associated with ambulance routing for critical healthcare services. The specific contribution of this paper can be described with the help of the following points:

- In this study, we considered SLAs for the assurance of critical healthcare services. Therefore, SLAs were considered in terms of the requested service time and MTTF of service (MTTF_s). These SLAs support the criticality constraint for routing a smart vehicle with service assurance.
- This study also considers the energy constraint for the continuity of service. Energy continuity plays a major role in critical healthcare services. In this study, green energy was considered to support the global issues of environmental degradation and global warming. Energy cooperation helps the sustainable services of smart vehicles to be provided to users.
- The proposed model can be useful in critical healthcare services as well as in general transport and business services, in which time and energy are the major factors for growth.
- The usefulness of the proposed model was demonstrated using various performance parameters. The results indicate that the variations in the SLA and energy play an important role in the selection of critical healthcare routing services.

The remainder of this paper is organized as follows. The related work and preliminaries for the proposed system model are presented in Sect. 2. Section 3 includes the proposed system model and its performance analysis. The theoretical results are explained with the help of an example in Sect. 4. The flow chart, algorithm, and time complexity analysis of the proposed approach is provided in Sect. 5. The experimental setup, results, and discussion are presented in Sect. 6. Section 7 includes the conclusions.

2 Related Work and Preliminaries

2.1 Related Work

The allocation of the shortest and quickest route is a major component of research in transport systems [24,25]. Currently, when deciding the shortest route for vehicle routing, users demand the fulfillment of service satisfaction and energy consumption. Therefore, numerous extensions have been developed to determine the shortest route for vehicle routing problems, such as the shortest route with arc failure [26], time-dependent vehicle routing with flexibility [27], quickest route with minimum traffic congestion [28], shortest route with information of mashups [29], and route planning for military ground battle vessels [30].

In [31], an approach is presented for dynamic vehicle routing. The approach deals with the delivery of urgent goods. Furthermore, a new proactive approach is provided in [32] to improve customer service requests for real-time control and forecasting. In [33], the quality of service of an ambulance is considered for developing an online smart transportation system for assisting ambulance services. The scheme proposed in [33] was further enhanced in [34] by introducing SLAs for the planning of smart transportation. Recently, concept in [34] was exploited for tour planners [35]. An energy-efficient routing mechanism was proposed by the authors in [36] for time-aware road networks. The approximation algorithm with the branch-and-bound strategies has been used for routing in real-time dense networks.

The authors in [37] propose SLAs for critical services, where a service provider can be penalized for not performing a service. In 2017, an exhaustive review was made in [38] to maximize the population coverage of ambulance services for advanced life support. The authors in [39] proposed schemes for urgent computing transport by using certain parameters, such as policing, SLAs, and data placement. Recently, the authors in [40] proposed critical healthcare ambulance routing by using the Internet-of-Things perspective. The authors in [40] proposed a real-time approach for implementing vehicle routing with gridlock information. A new trend in green energy for battery-operated vehicle routing schemes is discussed in [41–43]. A transport system for continuous and sustainable green routing based on the hybrid ant colony algorithm was developed in [44].

A rigorous review of green road freight systems was performed in [45]. The authors in [46] proposed an approach for green vehicle routing in urban areas by using the neuro-fuzzy model. Moreover, the authors in [47] proposed a mathematical model for one-to-one pickup and delivery in a road transport system. The authors of [22] demonstrated the role of information and communication in healthcare services by studying different perspectives and challenges. The usefulness of transport systems with green vehicle routing and a time boundary has been provided in [48,49]. The aforementioned discussed literature indicates that researchers are concerned with several critical healthcare service issues, such as service expectations, environmental conditions, optimal transport service planning, and homecare. The literature indicates that although technology has evolved at a considerable rate, there still exist gaps in evolving certain issue together for the uplift the society and various transport services. Recently, the concept of ambulance routing with an advanced technology has been named as social internet of vehicles (SIoV) [50]

In this study, we attempted to incorporate public and global issues, namely green energy cooperation and service experience, in terms of SLAs. To the best of our knowledge, no literature is available in which SLA and energy cooperation are discussed together with the aspects of critical healthcare services. In this study, we attempted to incorporate all the critical healthcare service parameters in existing traditional healthcare services by using innovative technology. To visualize the innovation, we presented the results by performing the proposed algorithm on various topologies.

2.2 Preliminaries

Let us assume, a road network is denoted as a graph $G = (N, E)$ where (N) is denoted as a set of (n) number of stations and (E) is denoted as a set of (m) number of links. In a road network, there are a number of stations, and let (u) and (v) are the two different stations of the road network and the connectivity between them is denoted as the link (u, v). Here, we are representing the nodes with stations for the better understanding with road networks. In this paper, sometime route is used instead of path for the ambulance routing. Also, vehicle (V) is referred here to ambulance vehicle and (SV) referred here for smart ambulance vehicle with constraints.

Let vehicle (V) is leaving from the source station (s) and reached at the destination station (t). A road network is known to several parameters associated with each link, i.e., $(u, v) \in E$ between stations (u and v) such as the delay and capacity of a link between two stations $d\,(u, v)$ and $c\,(u, v)$, respectively. The delay of the link (u, v) is the lag offered to the vehicle to traverse along the link (u, v) and the capacity of a link is the bottleneck function of a route which represents the bandwidth associated with the link (u, v) with a constant speed (ρ).

Let, a route (P) is the route from the leaving station $(s = u_1)$ to destination station $(t = u_k)$ which is the combination of different stations and links and is given by $P = (s = u_1, u_2, \ldots, u_k = t)$ such that $u_i \in N, i = 1, 2, \ldots, k$ and $(u_i, u_{i+1}) \in E, i = 1, 2, \ldots, k - 1$. Let us assume that a vehicle $(V)$is transported over the link (u, v) with constant speed (ρ) such that $\rho \le c\,(u, v)$ experience the $\left[d\,(u, v) + \frac{V}{\rho}\right]$ transportation time from the station (u) to (v) along the link (u, v). This transportation time is occurred minimum at the value of $\rho = c\,(u, v)$, and therefore, the above expression specifies the minimum transportation time experienced by the vehicle (V) and shows as [40,51,52]:

$$T_V\,(u, v) = \left[d\,(u, v) + \frac{V}{c\,(u, v)}\right] \tag{1}$$

The above expression shown in Eq. (1) represents the minimum transportation time experienced by the vehicle (V) between two stations, and by using applications of circuit switching technique, it is assumed that vehicle is being transported with a constant speed from leaving station (s) to destination station (t) without any store and forward mech-

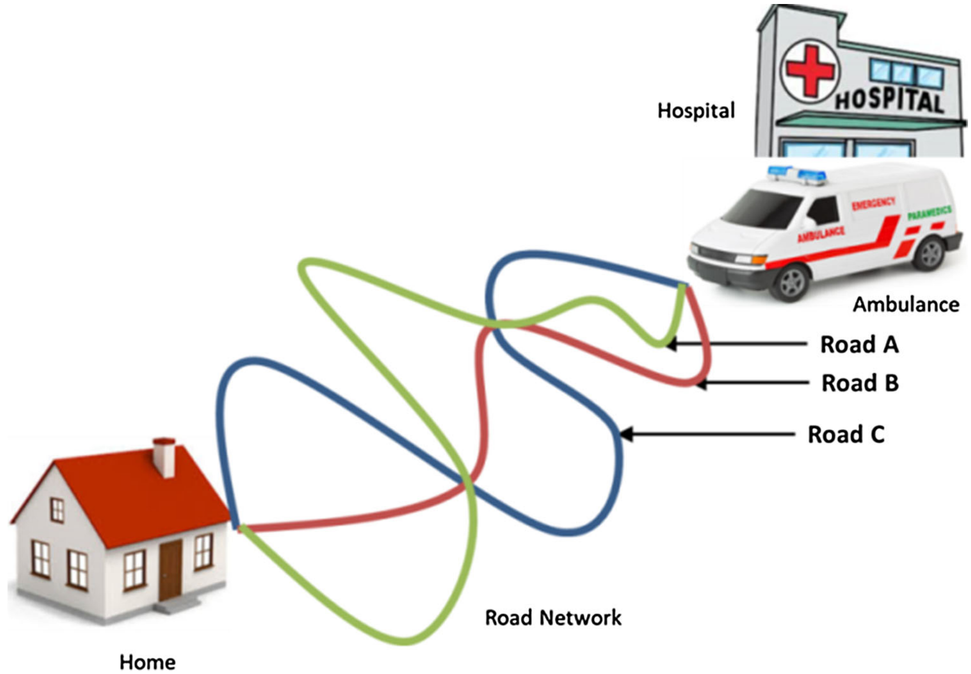

Fig. 1 Simple ambulance HTH routing without constraints [40]

anism. Therefore, minimum transportation time along s–t route (P) is given as [40]:

$$T_V(P) = \left[d(P) + \frac{V}{c(P)} \right]. \tag{2}$$

The first part of Eq. (2) represents the delay occurred along the route (P), and the denominator of the second part in the equation shows the bottleneck capacity of the route (P) [40,52]:

$$d(P) = \sum_{i=1}^{k-1} d(u_i, u_{i+1}) \tag{3}$$

$$c(P) = \min_{i=1,2,\ldots,k} c(u_i, u_{i+1}). \tag{4}$$

In Fig. 1, the traditional method of HTH services has been shown, where routing of vehicle has been done with the very less information of the network infrastructure. Therefore, sometimes, the services offered are getting failed or violated or unreachable.

By using Eqs. (1–4), the problem of minimum transportation time for the existing transitional method is formulated as [53]:

$$\begin{array}{c} \min T_V(P) \\ \text{Subject to } P \text{ is an } s{-}t \text{ route in network } G. \end{array} \tag{5}$$

Remark Here, at this point, it is worth to point and mention that the principle of optimality is not followed by the QPP problem. The principle of optimality is defined as if a route (P) is optimal, then it is not necessary that its sub-route will be optimal.

The information provided in this section enables us to use the proposed system model to incorporate advancements in the traditional methods of critical healthcare services.

3 Proposed System Model

The following assumptions are considered for proposing the system model:

1. The transportation of vehicle follows the conservation law.
2. The road capacities are statistically independent.
3. There are no loops in the road networks for the routes or paths.
4. Batteries are replaced\refilled at each station for continuous service.

Online home delivery services, such as pizza delivery, home healthcare courier delivery, and online shopping delivery, use intelligent transport systems to provide customers satisfaction with their services. Therefore, SLAs have been used in online businesses [6]. SLAs vary according to the application, and each service has its own SLAs. SLAs can be of different types, such as the service time (t_s), MTTF_s, and up time. We considered the MTTF_s and service time as SLAs. To compete with SLAs, each link in the road networks was associated with certain failures. To deal with these failures, the average failure time was considered in terms of the MTTF of a link (MTTF (u, v)) in the road networks. In the road networks, there exist numerous different stations and links and each link is associated with certain parameters. The proposed system model considers road networks in which the vehicle is smart with the certain useful information, such as the route SLAs, energy associated with vehicles, and gridlock time. Sometimes, the link parameters associated with a particular link are also considered as a factor of transportation failure when transport is not completed within a specific time [54]. Therefore, the link parameters are modeled with SLAs.

3.1 SLA Mapping and Cooperation

In the road transport network, the link between two stations is long in distance. Therefore, service time (t_s) and MTTF$_s$ are considered in hours. The road network already deals with the physical reliability of routes. Therefore, to deal with the failure due to performance factors, the SLAs are modeled using the requested service performance factor (RSPF), which is comparable to the route or link reliability. The RSPF is calculated as follows:

$$r_u = e^{-\frac{t_s}{\mathrm{MTTF}_s}}. \tag{6}$$

Therefore, from the two ideal cases, it is shown that the SPF lies in between minimum (0) and maximum (∞), which is comparable to link reliability.

An s–t route (P) is combination of multiple links. If any of the links are violated in the SLA, the entire SLAs are violated. Therefore, cooperating the SLAs between consecutive stations is more realistic than cooperating the SLAs over the entire route (P). Each station is associated with an RSPF. For performance failure, each station is associated with free transportation of a smart vehicle (SV) at a constant rate (ρ). Without loss of generality, the SLA cooperation is given as follows:

$$e^{\frac{-\left[d(u,v)+\frac{\mathrm{SV}}{\rho}\right]}{\mathrm{MTTF}(u,v)}} \geq r_u, \forall (u, v) \in E \tag{8}$$

The aforementioned equation provides SLA cooperation. If a link does not follow this condition, the transportation of a smart vehicle cannot support SLAs. Therefore, the transportation of smart vehicles from this link can be removed. For an SLA cooperative route, the SPF is calculated as follows:

$$R_s(P) = e^{-\left[\frac{d(P)+\frac{\mathrm{SV}}{c(P)}}{\mathrm{MTTF}(u,v)}\right]} \tag{9}$$

The surplus value of SPF is termed as the surplus service performance factor (SSPF). The SSPF ($r_u(SV, P)$) at station (u) along route (P) is calculated as follows:

$$r_u(SV, P) = \begin{cases} -\ln(r_u) - \left\{ -\ln\left[e^{\frac{-\left[d(u_i,u_{i+1})+\frac{\mathrm{SV}}{c(P)}\right]}{\mathrm{MTTF}(u,v)}} \right] \right\}, & \text{if } u = u_i, i = 1, 2, \ldots, k-1 \\ -\ln(r_u) & \text{otherwise} \end{cases} \tag{10}$$

By using the value of the link parameters, the service performance factor (SPF) of a link between two stations (u, v) is given as follows:

$$r_s(u, v) = e^{-\left[\frac{d(u,v)+\frac{\mathrm{SV}}{c(u,v)}}{\mathrm{MTTF}(u,v)}\right]}. \tag{7}$$

To authenticate the SPF which is made comparable to the RSPF and link reliability, the SPF is divided into two cases:

Ideal Case-1: Considering the SPF, if transportation time is minimum approximately equal to zero, i.e., $T_{\mathrm{SV}}(u, v) \cong 0$, then the SPF is calculated approximately equal to 1, hence the value of SPF is maximum.

Ideal Case-2: Considering the SPF, if transportation time is minimum approximately equal to one, i.e., $T_{\mathrm{SV}}(u, v) \cong \infty$, then the SPF is calculated approximately equal to 0, hence the value of SPF is minimum.

Remark In the aforementioned equation, the route capacity is considered different to the link capacity because the equation implies that the sub-road network of the roads is sorted with the help of different capacities associated with the network. Therefore, the capacity of the route in the sub-road network is the same as the sorted capacity.

The s–t route (P) is feasible only if the condition $r_u(SV, P) \geq 0, \forall u \in P$ is satisfied. The explanation for this condition is for the satisfaction of SLAs as noted at station to transport the smart vehicle with the rate of $c(P)$. Hence, the SLA cooperative quickest route is modeled as follows:

$$\begin{aligned} &\min_P T_{\mathrm{SV}}(P) \\ &\text{s.t. } r_u(SV, P) \geq 0,\ u \in P \\ &P \text{ is an } s-t \text{ route in network } G. \end{aligned} \tag{11}$$

The special characteristics of the SLA cooperative quickest route allow us to develop an algorithm that solves the quickest route with the guarantee of SLA satisfaction without any violations.

In the following subsection, energy cooperation is considered. Energy cooperation strengthens the service continuity.

3.2 Energy Cooperation

In the road network, the consumption of energy by the vehicle along with the link (u, v) is maintained so that the energy endowed with the smart vehicle (SV) [6] is enough to transverse that link (u, v). Let, each link $(u, v) \in E$ is associated with an energy rate $\varphi(u, v) > 0$, which is required by SV at station (u) to transport the smart vehicle along the link (u, v) and measured in per unit time. The energy across the link depends on the characteristics of links such as transport delay, link capacity.

As smart vehicle (SV) is associated with the fixed amount of energy, i.e., battery, and if it is marked at each station $(u \in N)$, then each station is mapped with this associated energy (F_u) at each station (u). If a smart vehicle is moving with constant speed (ρ) from station (u) to (v), then it is considered that smart vehicle is active at station (u) upto station (v), i.e., transported the smart vehicle in $\left(\frac{\mathrm{SV}}{\rho}\right)$ unit time. Therefore, the energy required at station (u) is given as $\left(\varphi(u, v)\frac{\mathrm{SV}}{\rho}\right)$. From the idea of energy cooperation and without loss any generality, let us assume the following equation [6,54]:

$$\varphi(u, v)\frac{\mathrm{SV}}{\rho} \le F_u, \quad \forall (u, v) \in E \tag{12}$$

The above equation depicts the energy cooperation, and if link does not follow this condition, then the transportation of vehicle cannot support to continuous services. Therefore, the transportation of the vehicle from this link can be removed.

Now, by using the mechanism of continuous transportation of smart vehicle along the s–t route (P) at a constant rate $c(P)$, then the total energy along the route (P) is calculated as:

$$E_{\mathrm{SV}}(P) = \sum_{i=1}^{k-1}\varphi(u_i, u_{i+1})\frac{\mathrm{SV}}{c(P)} \tag{13}$$

Let energy rate along the route (P) is denoted by $W(P) = \sum_{i=1}^{k-1}\varphi(u_i, u_{i+1})$. The remaining value of the energy is termed as residual energy supply (RES). This supply presented as $F_u(SV, P)$ at station (u) along the route (P) and is calculated as:

$$F_u(SV, P) = \begin{cases} F_u - \varphi(u_i, u_{i+1})\frac{\mathrm{SV}}{c(P)}, & \text{if } u = u_i, i = 1, \ldots, k-1 \\ F_u & \text{otherwise} \end{cases} \tag{14}$$

Remark In the above equation, the route capacity is considered rather than the capacity of link because this equation implied for the sub-network of the road network which is sorted with different capacities of the network. Therefore, the capacity of a route in the sub-road network is the same as of the sorted capacity, i.e., $c(P)$.

The s–t route (P) will be feasible if and only if the condition shown in the above equation, i.e., $F_u(SV, P) \ge 0, \forall u \in P$ followed. The explanation for this feasibility condition is given by the measurement of availability of energy as noted at each station to transport the smart vehicle with route capacity $c(P)$. Hence, the energy cooperative quickest route is modeled as below:

$$\begin{aligned} &\min_P T_{\mathrm{SV}}(P) \\ &\text{s.t. } F_u(SV, P) \ge 0,\ u \in P \\ &P \text{ is an } s-t \text{ route in network } G \end{aligned} \tag{15}$$

The special characteristics of the energy cooperative quickest route allow us to develop an algorithm that solves the quickest route with the guarantee of fuel availability without any discontinuity.

Figure 2 depicts that the transitional method of critical healthcare services is incorporated with the requested SLA parameters and energy constraints. Figure 2 supports the smart ambulance routing model for critical healthcare services, where the information regarding the road infrastructure is available with the smart vehicle.

SLA energy cooperation allows us to combine the characteristics of the two models in Eqs. (11) and (15) and formulate the constraint model of the SLA-energy cooperative quickest route (SEQR) as follows:

$$\begin{aligned} &\min_P T_{\mathrm{SV}}(P) \\ &\text{s.t. } r_u(SV, P) \ge 0, u \in P \\ &F_u(SV, P) \ge 0, u \in P \\ &P \text{ is an } s-t \text{ route in network } G \end{aligned} \tag{16}$$

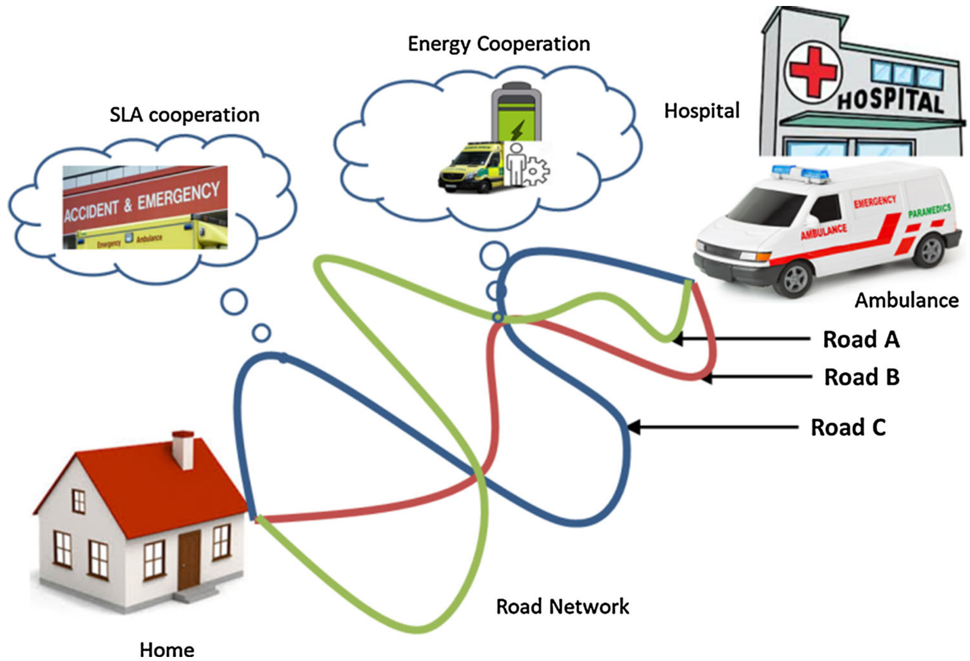

Fig. 2 Critical ambulance HTH routing with SLA and energy constraints

4 Theoretical Results

In general, let us assume that transport network associated with r different capacities arranged in increasing order such that $c_1 < c_2 < \cdots < c_r$. For cooperation of SLA and energy with links, let us find the minimum SLA and energy link capacity. The minimum SLA cooperative capacity is given as follows:

$$c_{\min\mathrm{SLA}}(u, v) = \min_{i=1,\ldots,r}\left\{c_i : e^{\frac{-\left[d(u,v))+\frac{\mathrm{SV}}{c_i}\right]}{\mathrm{MTTF}_s}} - r_u \geq 0\right\} \tag{17}$$

The procedure for SLA cooperation is shown as below which is helpful to implement in the proposed model.

Procedure: SLA Cooperation

Input: A network $\boldsymbol{G}(\boldsymbol{N}, \boldsymbol{E})$, capacity, delay and mean time to failure $(\boldsymbol{c}, \boldsymbol{d}, \boldsymbol{MTTF_s})$, respectively, Connection request $\mathbf{s} - \mathbf{t}$, Requested SLA $(\mathbf{t_s})$ and $\boldsymbol{MTTF_s}$.
Output: SLA Cooperation
Begin {
1. At each station, calculate the RSPF $(\boldsymbol{r_u})$
2. Calculate the SPF at each link with different capacities.
3. Find minimum SLA cooperative capacity of a link, i.e., $\boldsymbol{c_{minSLA}}$ $(\boldsymbol{u},\boldsymbol{v})$ after satisfying the condition of SSPF in Eq. (17).
} End

Corresponding to the energy cooperation, the minimum link capacity is given:

$$c_{\min E}(u, v) = \min_{i=1,\ldots,r}\left\{c_i : F_u - \varphi(u, v)\frac{\mathrm{SV}}{c_i} \geq 0\right\} \tag{18}$$

The procedure for energy cooperation is shown below for the proposed algorithm.

Procedure: Energy Cooperation

Input: A network $\boldsymbol{G}(\boldsymbol{N},\boldsymbol{E})$, capacity, delay and energy rate $(\boldsymbol{c},\boldsymbol{d}, \boldsymbol{\varphi})$, respectively, Connection request $\boldsymbol{s} - \boldsymbol{t}$ and Power source as a battery at stations $(\boldsymbol{F_u})$.
Output: Energy Cooperation
Begin {
1. At each station, the power of battery resource $(\boldsymbol{F_u})$.
2. Calculate the energy at each link with different capacities.
3. Find minimum SLA cooperative capacity of a link, i.e., $\boldsymbol{c_{minE}}$ $(\boldsymbol{u},\boldsymbol{v})$ after satisfying the condition of RES in Eq. (18).
} End

The above equations shown in (17) and (18) give the minimum link capacity individually with respect to either SLA or energy. The SLA-energy cooperative minimum link capacity is given by following the AND rule shown in the equation below as:

$$c_{\min}(u,v) = \min\{[c_{\min E}(u,v) \ge c_a \ge c(u,v)] \\ \cap [c_{\min\mathrm{SLA}}(u,v) \ge c_b \ge c(u,v)]\}. \quad (19)$$

Here c_a and c_b are the capacities which lies in minimum link capacity to satisfy the SLA and energy, respectively. To find the common minimum capacity from both constraints, use intersection between the minimum capacities of Eqs. (17) and (18). Equation (19) shows the minimum link capacity corresponding to criticality and continuity of transportation such that $c_{\min\mathrm{SLA}}(u,v) > 0$ and $c_{\min E}(u,v) > 0$ by following the AND rule.

The procedure to implement the SLA energy cooperation using AND rule for the proposed algorithm is given below:

Procedure: SLA–energy cooperation using AND rule

Input: A network $\boldsymbol{G}(\boldsymbol{N},\boldsymbol{E})$, capacity, delay, energy rate and mean time to failure ($\boldsymbol{c},\boldsymbol{d},\boldsymbol{\varphi},\boldsymbol{MTTF}$), respectively, Connection request $\boldsymbol{s}-\boldsymbol{t}$, Requested SLA ($\boldsymbol{t_s}$), $\boldsymbol{MTTF_s}$ and power source as a battery at stations ($\boldsymbol{F_u}$).
Output: SLA energy cooperation using AND rule
Begin {
1. At each station, the requested service performance factor (RSPF($\boldsymbol{r_u}$)) and the power of battery resource ($\boldsymbol{F_u}$).
2. Calculate the service performance factor (SPF) and energy at each link with different capacities.
3. Find the minimum intersection of minimum SLA and minimum energy cooperative capacity of a link, i.e., $\boldsymbol{c_{min}}(\boldsymbol{u},\boldsymbol{v})$ after satisfying the condition in Eq. (19).
} End

Remark For the feasibility of s–t route (P), the route capacity has to follow the condition given as $c(P) \ge c_{\min}(u,v)$.

From Eq. (19), the road network is sorted into r number of different sub-networks as the road network is associated with r different capacities. The sorting is used to divide the road network by following the inequality as shown below for the route capacity $c(P)$.

$$c(u,v) \ge c_j \ge c_{\min}(u,v); \quad \text{where } j = 1,2,\ldots,r \quad (20)$$

After formulating theoretical results, the proof of certain lemmas, definitions, and theorems is the utmost required.

Lemma 1 *Let a route $P = u_1, u_2 \ldots, u_{k-1}, u_k$ is known as s–t route in the sub-road network; then that s–t route (P) is called as SLA-energy cooperative quickest route (SEQR).*

Proof To prove lemma 1, the route (P) is a s–t route in the sub-road network, and the capacity of route $c(P)$ follows the condition that $c(P) \ge c_j \ge c_{\min}(u_i, u_{i+1})$, where $i = 1,\ldots,k-1$. Therefore,

$$F_u(SV,P) = F_u - \varphi(u_i,u_{i+1})\frac{\mathrm{SV}}{c(P)} \\ \ge F_u - \varphi(u_i,u_{i+1})\frac{\mathrm{SV}}{c_{\min}(u_i,u_{i+1})} \ge 0$$

$$r_u(SV,P) = e^{\frac{-\left[d(u_i,u_{i+1})+\frac{\mathrm{SV}}{c(P)}\right]}{\mathrm{MTTF}(u,v)}} \\ -r_u \ge e^{\frac{-\left[d(u_i,u_{i+1})+\frac{\mathrm{SV}}{c_{\min}(u_i,u_{i+1})}\right]}{\mathrm{MTTF}(u,v)}} - r_u \ge 0$$

The stations which are not taking part in the transportation has no matter of concern and for the SLA-energy cooperative route SSPF, and residual energy has to follow these above dictated conditions. □

4.1 Illustration of Results

The theoretical illustration of the proposed model is presented on the benchmark network topology [55–58], which consists five stations and eight links. Each link is endowed with specific values as shown in Fig. 4. The parameters endowed with the links are delay, capacity, energy rate and MTTF (from left to right). At each station, certain fixed value of battery power (F_u) and RSPF (r_u) is associated (Fig. 3).

Using Eq. (19), sort the links with SLA-energy cooperative minimum capacity links. Figure 4a shows the links associated with minimum SLA-energy cooperative capacity and endowed capacity of link (from left to right) $(c_{\min}(u,v), c(u,v))$. In this topology, there are three different capacities present with the values of 20, 27 and 60 V/s. The numbers of different sub-networks are equal to the number of different capacities endowed with the network.

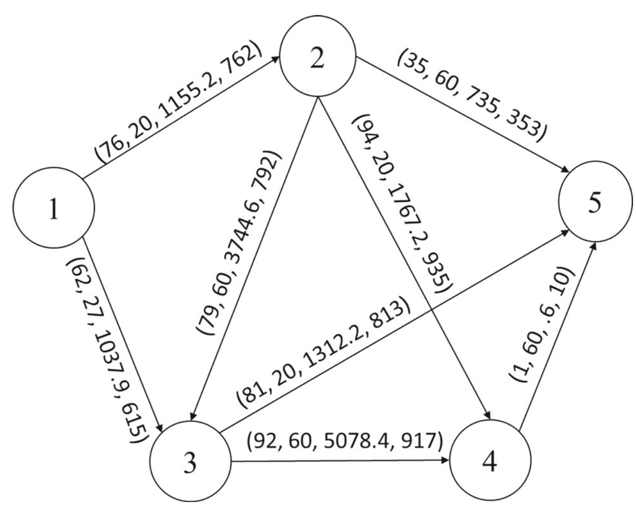

Fig. 3 Benchmark network topology $(G = (N,E))$, values of parameters (from left to right) delay, capacity, energy rate and mean time to failure (d, c, φ, MTTF). At stations, battery power, $F_u = 200$ kW and RSPF, $r_u = 0.8998$

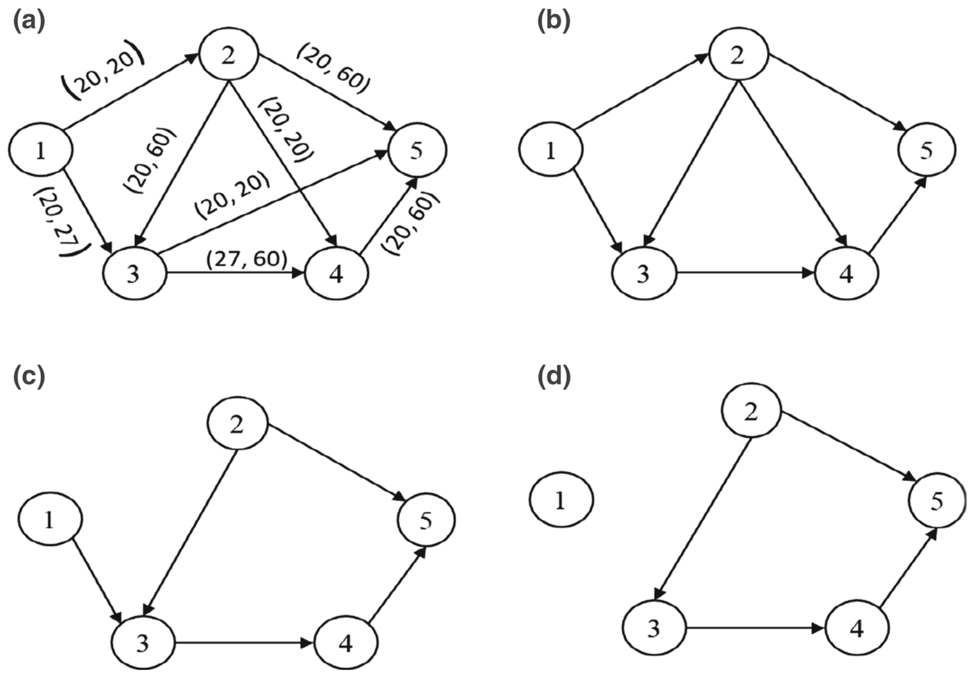

Fig. 4 **a** Network with link values $(c_{\min}(u,v), c(u,v))$. Sorted networks **b** G_1 **c** G_2 and **d** G_3

Figure 4b–d shows the sub-road networks sorted with the help of Eq. (20) for the maximum flow of traffic with route capacities of 20, 27, and 60 V/s.

By applying the quickest route problem, there are a number of different routes depending on the number of different road capacities. The topology in Fig. 4a shows the links with minimum SLA-energy cooperative capacity, and other term is shown as link capacity. Figure 4b–d shows the subnetwork with the SLA-energy cooperative capacities. The route 1 − −2 − −5 is the quickest route for the smart vehicle routing by applying these theoretical concepts of SEQR.

Lemma 2 *Let a s–t route P is said to be a feasible route with route capacity $c(P) = c_j$; then P is said to be a route in G_j.*

Proof From Lemma 1, let P is feasible.

$$F_u(V,P) = F_u - \varphi(u_i,u_{i+1})\frac{\mathrm{SV}}{c(P)} \geq 0, i = 1,2,\ldots,k-1$$

$$r_u(V,P) = e^{\frac{-\left[d(u_i,u_{i+1}) + \frac{\mathrm{SV}}{c(P)}\right]}{\mathrm{MTTF}(u,v)}} - r_u \geq 0, i = 1,2,\ldots,k-1$$

Hence, $c_{\min}(u_i,u_{i+1}) \leq c(P) = c_j \leq c(u_i,u_{i+1})$ where $i = 1,\ldots,k-1$, and (u_i,u_{i+1}) are in the route with sorted links of G_j, and hence, P is a s–t route.

This paper emphasis more on the critical and continues transportation route or path which depends on the quickest route computation using shortest path problem (SPP). Here, the utility of SPP is used with constraints; hence constraint SPP is used for the solutions using Dijkstra algorithm with link delay as a cost function in the sub-networks.

$$\mathrm{SPP}_j : \min_P d(P)$$
$$\text{s.t. } P \text{ is a } s{-}t \text{ route in the network } G_j \tag{21}$$

□

Lemma 3 *Let P be an optimal route solution of SPP_j and $c(P) = c_h > c_j$. Then, there is no other optimal solution for the SEQR with capacity c_j.*

Proof Let Q be a s–t feasible route for the SEQR route with capacity c_j then Q is a route in G_i.

$$T_{\mathrm{SV}}(P) = d(P) + \frac{\mathrm{SV}}{c_h} < d(Q) + \frac{\mathrm{SV}}{c_j} = T_{\mathrm{SV}}(Q)$$

Therefore, Q cannot be an optimal solution for the SEQR. □

Theorem 1 *Let $\check{P}$ be an optimal solution of the SEQR and $\left(\check{P}\right) = c_h$. Then, $\check{P}$ is an optimal solution of SPP_h and any optimal solution of SPP_h is an optimal solution.*

Proof Since $\check{P}$ is an s–t feasible route for the SEQR with capacity c_h, then $\check{P}$ is an s–t route in the G_h. Let (Q) be a s–t feasible route in the network G_h, then $c(Q) \geq c_h$. If $d(Q) < d\left(\check{P}\right)$, then

$$T_{\mathrm{SV}}(Q) = d(Q) + \frac{\mathrm{SV}}{c(Q)} < d\left(\check{P}\right) + \frac{\mathrm{SV}}{c_h} = T_{\mathrm{SV}}\left(\check{P}\right)$$

which contradict the optimality of route $\check{P}$. Furthermore, by applying the lemma 3, the capacity of any s–t shortest route $\tilde{P}$ in G_h is $c\left(\tilde{P}\right) = c_h$. Hence, $\tilde{P}$ is a s–t feasible route for SEQR such that $T_{\mathrm{SV}}\left(\tilde{P}\right) = T_{\mathrm{SV}}\left(\check{P}\right)$ is an optimal solution.

5 Flowchart, Algorithm, and Time Complexity

5.1 Flowchart

See Fig. 5.

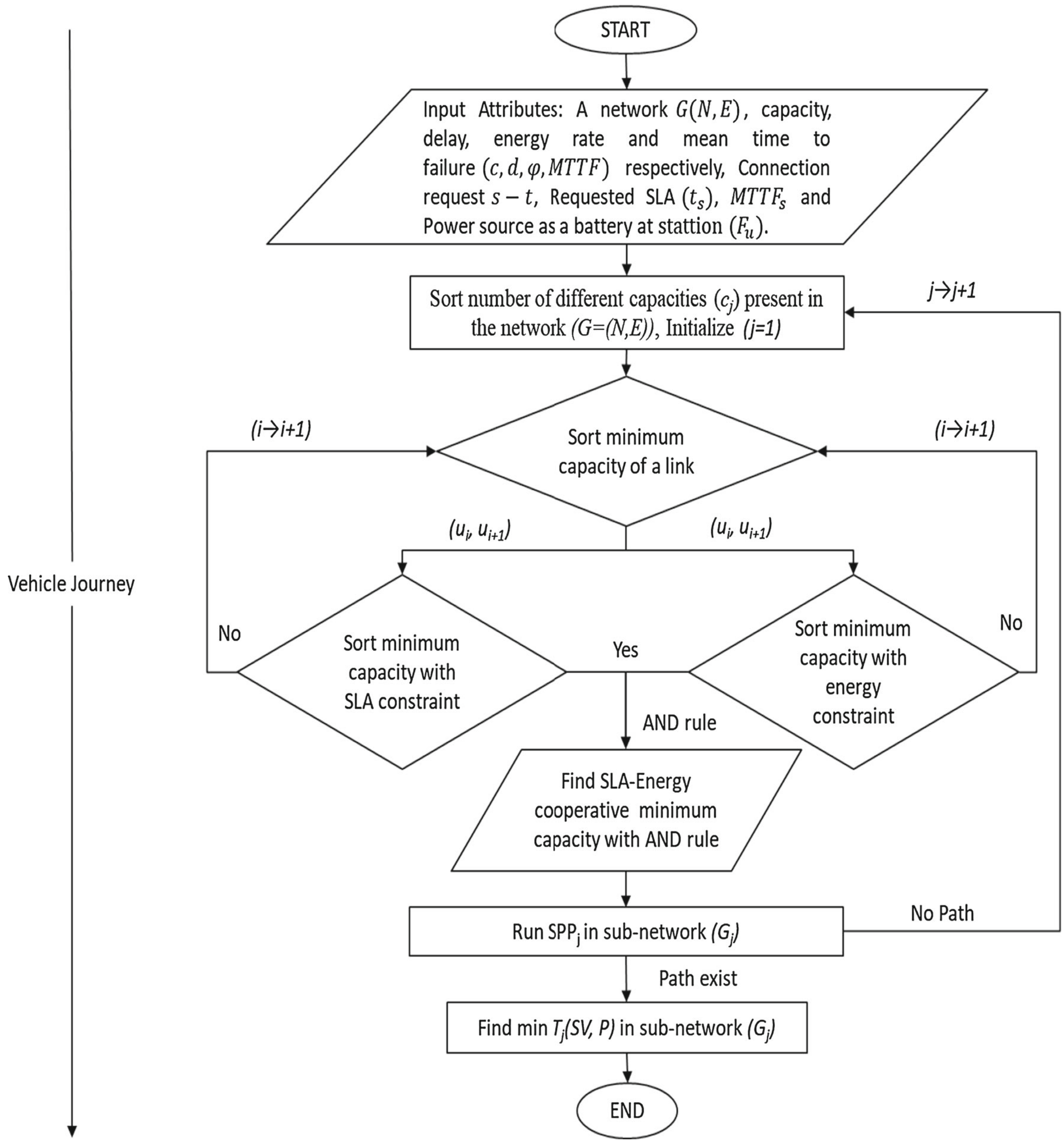

Fig. 5 Flowchart for the SEQR algorithm

5.2 Algorithm for SEQR

5.2 Algorithm for SEQR

Algorithm 1: SEQR Algorithm

Input: $G(N, E), V, c(u, v), d(u, v), MTTF(u, v), r_u, t_s$ and $MTTF_s$
Output: SLA-energy Cooperative Quickest Route (SEQR)
BEGIN{

Initialization:
$j \leftarrow 1,$
Procedure:
STEP0: Variable Declaration
$G \leftarrow$ Directed Network
$N \leftarrow$ Set of stations
$E \leftarrow$ Set of links
$c(u, v) \leftarrow$ Capacity of the link (u, v)
$d(u, v) \leftarrow$ Delay of link the (u, v)
$\varphi(u, v) \leftarrow$ Energy rate of link the (u, v)
$F_u \leftarrow$ Endowed energy or fuel with smart vehicle noted at station u
$r_u \leftarrow$ Requested service performance factor at station u
$SV \leftarrow$ Vehicle with constraints
$t_s \leftarrow$ Requested service time
$MTTF_s \leftarrow$ Mean Time to Failure of service
$MTTF(u, v) \leftarrow$ Mean Time to Failure of a link
STEP1: Prune r different capacities of links corresponds to critical-continuous service & label of minimum capacity:
(i) $c_1 < c_2 < c_3 \cdots < c_r$
(ii) $c_{min}(u, v)$ with AND rule
STEP2: Solve SPP_j w.r.t. delay time $d(u, v)$in G_j with capacities c_j
For $j \leftarrow 1{:}\, r$
    Set $j \leftarrow 1$
    Solve SPP_j
        If No $s - t$ route in $G_j$with capacity with c_j
            go to STEP3
        else
            Let P_j is an optimal solution for SPP$_j$with capacity$c(P_j) = c_j$
        end
    end
STEP3:
If $j = r$
    go to STEP4
else
    set $j = j + 1$ and go to STEP2
end
STEP4: Find the solution
Find index $h \in (1, 2, \ldots r)$ of route array P_j such that

$$T_{SV}(P_h) = \min_{j=1,\ldots,r} T_{SV}(P_j)$$

P_h is an optimal solution of the SEQR
} END

Table 1 Data table associated with link of 14-stations NSFNET

Link	MTTF (u, v)	$d\,(u, v)$	$c\,(u, v)$	$\varphi\,(u, v)$	Link	MTTF (u, v)	$d\,(u, v)$	$c\,(u, v)$	$\varphi\,(u, v)$
a_1	176	18	46	1490	a_{12}	960	96	31	28,570
a_2	272	27	24	1750	a_{13}	353	35	16	1960
a_3	65	6	16	58	a_{14}	59	6	87	313
a_4	199	20	46	1840	a_{15}	727	73	99	52,757
a_5	379	38	16	2310	a_{16}	587	59	39	13,576
a_6	629	63	17	6747	a_{17}	50	5	39	98
a_7	594	59	17	29,240	a_{18}	190	19	99	3574
a_8	838	84	84	11,995	a_{19}	239	24	26	1497
a_9	876	88	39	30,202	a_{20}	555	55	59	17,848
a_{10}	370	37	26	3559	a_{21}	641	64	39	15,974
a_{11}	433	43	87	16,086					

5.3 Complexity Analysis

Theorem 2 *The time complexity of the proposed SEQR algorithm is* $O(r\,(m + n\,(log\,(n))))$.

Proof The SEQR is explained in certain steps where step 0 is used to declare the variables. Step 1 is required to sort the sub-road networks after satisfying the SLA agreements and energy requirements. The different numbers of sub-road networks are sorted equal to the number of different capacities present in the road network. In step 2, prunes the SPF of the sorted links from different sub-networks and run the Dijkstra's algorithm SPP_j having the time complexity of $O\,(m + n\,(\log n))$ [59] in steps 3 and 4. This algorithm is run for the r different sub-road networks, and therefore, the complexity of the proposed algorithm is $O\,(r\,(m + n\,(\log\,(n))))$. Finally, in the last step 5, comments on the route with the minimum transportation delay are made.

6 Simulation Results and Discussion

6.1 Experiment Setup

The simulation was performed on a personal computer having the following configuration: CoreTMi5-7400 Intel(R) processor, 3.00 GHz CPU, 8 GB RAM, Windows 10 operating system, and MATLAB 2010a. Results were obtained for the implementation of the proposed SEQR algorithm, which uses the utility of the Dijkstra algorithm and is therefore solvable in polynomial time.

The standard 14-station NSFNET and 24-station USANET topologies [6,60] were used to implement the proposed algorithm. The simulation of the proposed SEQR algorithm required input parameters with specific values, as presented in Tables 1 and 2. The units of capacity and delay were considered as vehicle per hour (V/h) and hours (h), respectively. The units of $MTTF_S$ were taken as hours (h). The battery(F_u) with smart vehicle marked at each station was considered as 400 kW. The value of the energy rate at each link $(\varphi\,(u, v))$ was calculated using the relation $10^{-4}c\,(u, v)\,d^2\,(u, v)$. The unit of the energy rate was (kW/h). The SLAs considered for the transportation of smart vehicles between two consecutive stations over a link were the service time (t_s) and MTTF_s of the smart vehicle. The units of both the parameters was hours (h). The SLA values considered in this study were $t_s = 105$ h and $\text{MTTF}_S = 1000$ h (Figs. 6, 7).

The proposed algorithm was also used on random network topologies generated through the Waxman random topology generator. Different values of capacity and delay were generated from the random uniform distribution range of [1, 100]. The value of the $MTTF(u, v)$ was also generated from the random uniform distribution range of [1, 1000]. The pattern of the qualifying set of routes varied for different values of the power and RSPF.

6.2 Simulation Results

The simulation results for both the standard networks are given in Tables 3 and 4. The selection of the minimum transportation routes depends majorly on SLA energy cooperation. In the first column of Tables 3 and 4, the capacity of the route is indicated. Corresponding to these values, the route opted for the transportation of the smart vehicle is presented in the second column. Each route contains the value of the transportation time given in column 3. According to the transportation time, comments are provided on the route with the minimum transportation time in the last column of both tables.

The results were extended by using random networks so that the performance of the proposed algorithm could be evaluated accurately. Random topologies were generated using the Waxman topology generator [61,62].

Table 2 Data table associated with link of 24-station USNET

Link	MTTF (u, v)	$d\ (u, v)$	$c\ (u, v)$	$\varphi\ (u, v)$	Link	MTTF (u, v)	$d\ (u, v)$	$c\ (u, v)$	$\varphi\ (u, v)$
a_1	139	14	3	59	a_{23}	89	9	11	89
a_2	415	42	34	5998	a_{24}	655	66	50	21,780
a_3	305	30	72	6480	a_{25}	59	6	14	50
a_4	190	19	14	505	a_{26}	553	55	67	20,267
a_5	607	61	66	24,559	a_{27}	147	15	49	1103
a_6	65	6	11	40	a_{28}	342	34	34	3930
a_7	370	37	57	7803	a_{29}	166	17	52	1503
a_8	988	99	67	65,667	a_{30}	200	20	19	760
a_9	442	44	66	12,778	a_{31}	444	44	44	8518
a_{10}	630	63	14	5557	a_{32}	958	96	34	31,334
a_{11}	553	55	53	16,033	a_{33}	170	17	14	405
a_{12}	575	58	72	24,221	a_{34}	412	41	66	11,095
a_{13}	174	17	25	722	a_{35}	540	54	90	26,244
a_{14}	171	17	18	520	a_{36}	718	72	18	9331
a_{15}	154	15	93	2092	a_{37}	771	70	94	55,733
a_{16}	890	89	49	38,813	a_{38}	340	34	72	8323
a_{17}	625	63	34	14,685	a_{39}	522	52	25	6760
a_{18}	397	40	37	5440	a_{40}	95	10	52	520
a_{19}	735	73	67	35,704	a_{41}	877	88	18	13,939
a_{20}	999	100	99	99,000	a_{42}	948	95	50	45,125
a_{21}	422	42	3	529	a_{43}	657	66	25	10,890
a_{22}	522	52	19	5138					

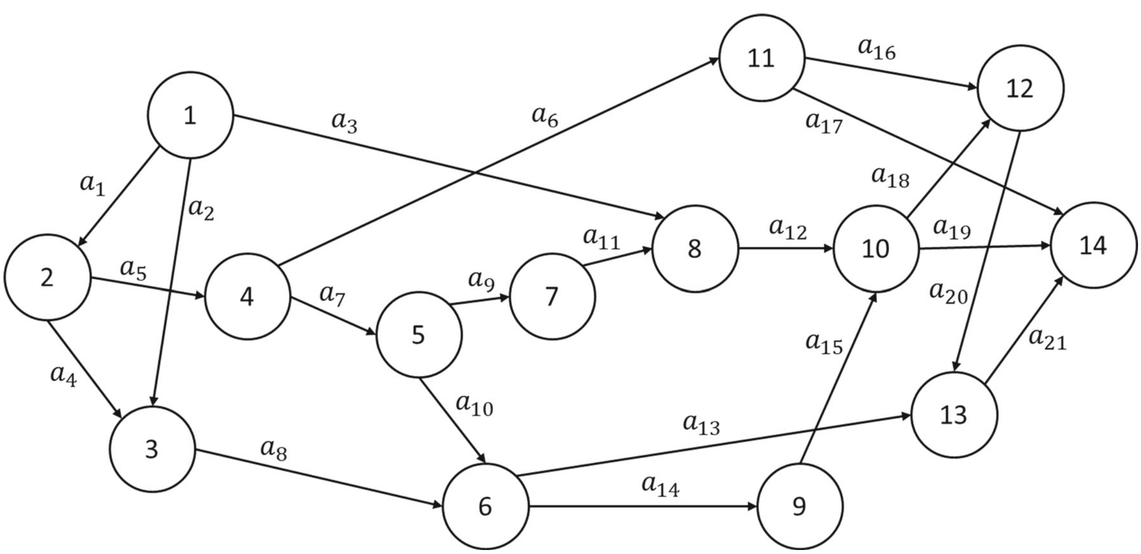

Fig. 6 The 14-station NSFNET

Different parameters were used to compare the relative performance values. We analyzed the performance parameters in terms of the mean candidate s–t QSS routes, average hop count, and average energy efficiency. The mean candidate s–t QSS route was used for obtaining the mean number of candidate optimal s–t quickest routes for the service. The average hop count is the performance measure for determining the energy efficiency. If the average hop count decreases, the average energy efficiency increases. The energy efficiency is the performance measure for the efficient use of energy by a smart vehicle. The energy efficiency is the ratio of energy used by the smart vehicle in transportation to the total energy associated with the smart vehicle marked at each station.

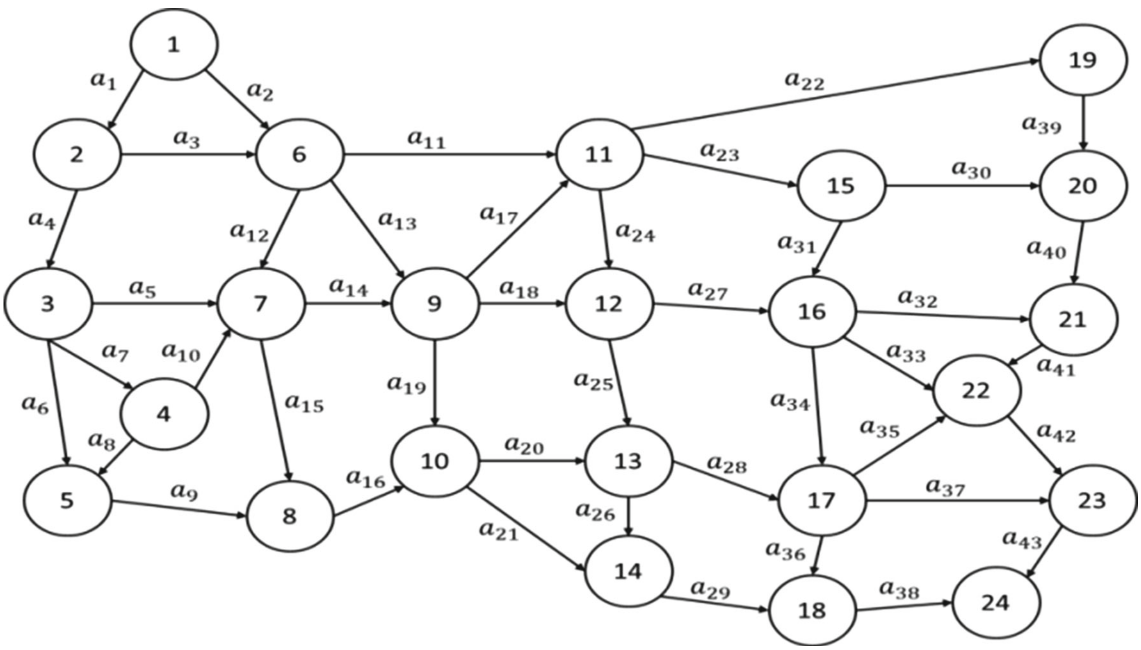

Fig. 7 The 24-station USANET

Table 3 Results of the SEQR algorithm for the 14-stations NSFNET topology

Capacity	Selected route	$T_{\sigma}\ (P)$	Comment
16	1–2–4–11–14	124.0625	Minimum
17	1–3–6–9–10–14	214.0588	No
24	No route	INF	No route
26	No route	INF	No route
31	No route	INF	No route
39	No route	INF	No route
46	No route	INF	No route
59	No route	INF	No route
84	No route	INF	No route
87	No route	INF	No route
99	No route	INF	No route

Table 4 Results of the SEQR algorithm for the 24-station USNET topology

Capacity	Selected Route	$T_{\sigma}\ (P)$	Comment
3	1–6–9–12–16–17–18–24	261.3333	No
11	1–6–9–12–13–14–18–24	211.0909	No
14	1–6–9–12–13–14–18–24	211.0714	Minimum
18	1–6–9–12–16–17–18–24	261.0556	No
19	1–6–9–12–16–17–23–24	298.0526	No
25	1–6–9–12–16–17–23–24	298.0400	No
34	1–6–7–8–10–13–14–18–24	410.0294	No
37	No route	INF	No route
44	No route	INF	No route
49	No route	INF	No route
50	No route	INF	No route
52	No route	INF	No route
53	No route	INF	No route
57	No route	INF	No route
66	No route	INF	No route
67	No route	INF	No route
72	No route	INF	No route
90	No route	INF	No route
93	No route	INF	No route
94	No route	INF	No route
99	No route	INF	No route

The first, second, and third columns of Tables 5, 6, and 7 represent the variation in the number of capacities, stations, and links associated with the networks, respectively. The variation in the mean number of candidate *s*–*t* qualifying service set (QSS) routes, average hop count, and average energy efficiency is indicated in the fourth, fifth, and sixth columns of Tables 5, 6, and 7, respectively.

6.3 Discussion

6.3.1 Standard Network Topologies

The proposed algorithm has been implemented over the standard topologies 14-station NSFNET and 24-station USNET with their link values as shown in table. The results have been shown in the table. The 14-stations NSFNET and 24-stations USNET compute the SLA-energy cooperative route for crit-

Table 5 The simulation parameters and the mean candidate s–t QSS routes for the SEQR algorithm

r	n	m	Mean candidate $\mathbf{s}-\mathbf{t}$ QSS routes for 10 runs								
			$F_u = 10$			$F_u = 100$			$F_u = 1000$		
			$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$
10	100	4600	6.4	8.5	8.7	8.9	9.4	9.5	9.1	9.5	9.8
	200	18,500	7.8	9.2	9.2	9.3	9.6	9.4	9.3	9.4	9.4
	400	74,000	8.4	8.8	9.2	9	9.4	9.8	9.2	9.4	9.6
100	100	4600	38	52.7	54	56.6	61	62.6	58.5	59.9	60.7
	200	18,500	49.8	56.6	56.7	58.5	60.8	61.6	59.1	61.8	62
	400	74,000	60	60.5	62	64.5	62.5	62.5	88	92.4	94.2
1000	100	4600	63.9	80.6	82.6	89.6	95.7	95.3	90.5	95.6	96.2
	200	18,500	72.6	89.6	90	92.8	96.4	97.6	94.2	97.4	98
	400	74,000	88.5	90.6	91	92.4	94	94.3	95.1	96.8	98

Table 6 The simulation parameters and the average hop counts for the optimal route for the SEQR algorithm

r	n	m	Average hop counts for the optimal route for 10 runs								
			$F_u = 10$			$F_u = 100$			$F_u = 1000$		
			$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$
10	100	4600	2.8	2.7	2.8	2.5	2.7	3.6	2.9	2.3	2.9
	200	18,500	3	2.8	2.5	2.6	2.5	2.4	2.7	2.5	2.3
	400	74,000	3.6	3.4	3.2	3.2	3.4	3.4	3	3	2
100	100	4600	4.1	2.7	2.6	2.9	2.6	2.6	2.9	2.6	2.5
	200	18,500	3.2	3.1	2.9	3.6	3	2.8	3.1	3	3
	400	74,000	4.5	4	3.5	3	2.5	2	4.5	3	2.8
1000	100	4600	2.5	2.4	2.3	3.2	2.7	2.5	3.2	2.3	2.2
	200	18,500	2.8	2.4	2.6	3.6	2.8	2.6	3.6	2.8	2.6
	400	74,000	3.9	3.8	2.5	3.3	3	2.8	3.6	3.2	3.2

Table 7 The simulation parameters and the average energy efficiency for the optimal route for the SEQR algorithm

r	n	m	Average energy efficiency for the optimal route for 10 runs								
			$F_u = 10$			$F_u = 100$			$F_u = 1000$		
			$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$	$t_s = 100$	$t_s = 105$	$t_s = 110$
10	100	4600	0.36333	0.90749	1.22174	0.39798	1.0771	1.19586	0.3498	1.9055	1.9706
	200	18,500	1.05942	2.01246	4.28012	1.75267	1.82279	7.35506	0.4624	1.69919	3.94239
	400	74,000	1.00162	3.3933	4.60966	3.82324	4.5407	6.28248	2.5712	5.707	5.744
100	100	4600	0.44407	0.51382	1.04791	0.55043	0.58404	1.53078	0.6695	0.84102	1.20749
	200	18,500	0.90359	1.3701	1.68088	1.34248	2.03887	2.49683	2.2992	2.12448	2.6691
	400	74,000	0.40265	1.3386	5.5728	2.99975	2.36895	3.74615	1.5138	3.5489	4.3569
1000	100	4600	2.66702	1.27768	1.51618	0.54678	1.13749	1.26496	0.4201	1.83122	2.67396
	200	18,500	0.4552	2.03994	2.6679	0.6947	1.6202	2.7475	0.8940	0.92748	1.39722
	400	74,000	1.5689	2.0695	4.3663	0.6875	1.5423	3.2595	0.3624	0.5983	1.7999

ical healthcare ambulance routing as $1-2-4-11-14$ and $1-6-9-12-13-14-18-24$. The capacity for the SLA-energy cooperative routes for the 14-station NSFNET and 24-stations USNET are opted as 16 and 14 V/h.

6.3.2 Random Topology Generator

Tables 5, 6, and 7 indicate the mean number of candidate s–t QSS routes, average hop count, and average energy efficiency of the optimal routes. The variation in each parameter with reference to the requested service time (t_s) and energy associated with the smart vehicle (F_u) is easily obtained from these tables.

Let us consider the fourth column of Table 5. The results are presented for a battery energy (F_u) of 10 kW and different SLA requested service times (t_s) for the ambulance service. When the number of capacities associated with the network was increased from 10 to 1000, the number of mean candidate s–t QSS routes for the service increased. This pattern was also analyzed for the variation in the number of nodes. As the number of nodes increased at a particular value of battery energy, the number of mean candidate s–t QSS routes for the service increased. The same pattern was observed for different values of the battery energy and SLA requested service time (rows in Table 5). The number of mean candidate s–t QSS routes for the service again increased.

Therefore, Table 5 indicates that the values of mean candidate s–t QSS routes for the service increased as the value of the requested service time increased. Moreover, if value of battery energy associated with the smart vehicle increased, the number of mean candidate s–t QSS routes also increased. This behavior indicates that as we increase the value of both constraints, the possibility of obtaining optimal s–t routes for the services also increases, which is a good result.

Another performance parameter considered for the proposed algorithm is the average hop count. The first row of Table 6 indicates that the number of nodes increased with an increase in the hop count. Moreover, at a battery energy of 10 kW, the hop count decreased as we increased the value of the requested service time, which indicates that the availability of direct routes increased. If we vary the battery energy, the hop count decreases, which indicates that nodes are available with suitable battery energy so that the smart vehicle can transport with minimum hops.

In conclusion, the average hop count indicates how fast a route can be obtained. The minimum hop count value indicates the efficient use of energy associated with the smart vehicle marked at each station. As we increased the value of the requested service time (t_s) and energy associated with the smart vehicle (F_u), the hop count decreased, which indicates that to obtain superior results, the SLA requested service time and energy associated with the smart vehicle must be high.

Table 7 indicates that the average energy efficiency increased as the values of the requested service time (t_s) and energy associated with the smart vehicle (F_u) were increased. This pattern can be easily visualized with respect to the average hop count. The lower the hop count, the higher is the energy efficiency because energy consumption occurs at each hop. The values in the first row indicate that the energy efficiency increased as the number of capacities, number of nodes, battery energy, and requested service time were increased.

Finally, the results indicate that as the service requested time, number of different capacities, number of nodes, and energy were increased, the possibility of obtaining an increased number of SLA-energy-satisfied QSS routes increased; however, the average hop count decreased. Tables 5, 6, and 7 indicate the usefulness of the requested service time (t_s) and energy associated with the smart vehicle (F_u) (which can be easily analyzed) for calculating the energy efficiency.

The simulation results indicate that if we consider both constraints together, critical healthcare services cannot be violated and are served consistently toward criticality. The proposed model is suitable for ambulance management which has a fleet of ambulances with different battery capacities. These ambulances can be managed through an awareness of criticality and suitable battery energy management.

7 Conclusion

In this study, a new variety of ambulance vehicle routing is presented using the quickest path problem (QPP) model. The constraints of SLAs and energy allow us to incorporate the criticality and continuity constraints. The problem is formulated as finding the quickest route for vehicle routing with the minimum transportation time corresponding to the sub-road networks (same as the number of different road capacities). These sorted sub-road networks satisfy both the SLA and energy constraints at each station for the routing of smart vehicle services. The proposed SEQR algorithm performs suitably without having a higher time complexity than the well-known Dijkstra algorithm. The results were obtained using several networks. Performance analysis justified the consideration of constraints for achieving the criticality and continuity of services. Furthermore, the requested service time (t_s) and energy associated with a smart vehicle (F_u) were varied to examine the usefulness of the performance parameters of the optimal routes, namely the mean number of candidate s–t QSS routes, average hop count, and average energy efficiency.

In summary, three conclusions can be drawn for better understanding the variations in the number of nodes, number of different capacities, battery energy, and requested service time:

- The mean number of candidate s–t QSS routes increased, which is useful for critical healthcare service routing and provides increased possibilities for services.
- The hop count decreased, which indicates that the smart vehicle is self-capable of delivering critical healthcare services without passing more number of stations.

- The energy efficiency increased, which indicated that the vehicle is associated with a considerably battery energy than the requested battery energy for critical healthcare services.

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