Effective Patient Scheduling For Public Health Events Based On Deep Reinforcement Learning

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ABSTRACT

Amidst the current worldwide pandemic of the novel coronavirus, there are still issues about the efficient allocation of emergency supplies and shortcomings in recovery protocols. To enhance individuals' health and overall welfare, it is imperative to enhance and refine the emergency patient scheduling framework for health emergencies while upholding the idea of a society with an inherent future for humanity. The paper proposed an Efficient Patient Scheduling for Public Health Emergencies (EPS-PHE) using Multiagent Reinforcement Learning (MRL). Originally intended to solve the PHE and improve EPS, the technology was conceived as a distributed multiagent system. MRL has proposed a decentralized incentive system evaluation technique for the EPS-PHE input. An incentive type called a Direct Incentive (DI) is used to show the relationships between individuals or details about two closely connected events. The quality of data transmission in EPS-PHE or the efficacy of the emergency network is measured using a Collective Incentive (CI). Simulation research has shown the value of the Deep Learning (DL) - MRL approach in EPS-PHE framework optimization.

1. Introduction

Several factors define an Emergency Department (ED), including the interdependence between the patient's clinical condition and the limited availability of medical resources. It is also impossible to anticipate what will happen in an emergency department since patients might arrive at any time [1]. Consequently, sufficient medical resources cannot be prearranged. Decision-makers may probably make errors that might affect the patient's treatment process because of the complex and unexpected nature of the problem [4]. In addition, if one decision is made incorrectly, the waiting time for patients might increase, leading to an overcrowded emergency room. Therefore, if patients had to wait longer in the emergency department, their health problems might worsen, which would be very bad.

Using a triage method may help classify patients to the emergency department in PHE [2]. Acuity is ranked 1 to 5 on the Australian Triage Scale (ATS) and the Canadian Triage and Acuity Scale (CTAS), where 1 is the least severe condition and five is the most life-threatening. Overcrowding in emergency rooms is a serious problem, and several efforts have been undertaken to solve it over the last few years. For instance, administrations have implemented quality and efficiency-related goals and measures [3]. Furthermore, a few institutions have instituted a fast-track system that sorts patients according to their urgent conditions, allowing for more targeted care [9]. However, problems with how long patients must wait in emergency departments continue.

Several academics have recently found important results from investigations and assessments of DL and the scheduling of patient resources across numerous industries. To control drone landings based on visual signals on the USV deck, Polvara et al. investigated a complex technique known as deep RL.

An outstanding navigational strategy for efficiently managing the two phases of flight—marker identification and downward operation—is proposed to utilize a hierarchical Deep Q-Network (DQN). The results of the simulations show how resilient the suggested method is to different ship-affecting shocks. The results are on par with cutting-edge algorithms using template alignment [5]. Using DL and massive amounts of statistical data from a large number of genomic aligners, another team of researchers has developed a way to anticipate protein residue interactions [6].

Using deep RL, Ojugo created a cutting-edge decision-support framework for the common incidence of diabetes [10]. By combining data mining with AI, we want to develop a predictive diagnostic strategy that can solve problems that traditional approaches can't at a reasonable cost [7]. It is crucial to analyze data patterns impacted by uncertainties and disruptions and replicate the model's ease of handling to find a cost-effective and trustworthy solution. As a potential tool for diabetes detection, the scientists looked at using a DL ensemble. The writers of [8] investigated the optimization model to schedule urban ED resources. They used the deep RL algorithm to conceptualize the ED resource distribution network's topology. They improved the system by using the DQN navigation algorithm, which improves the effective scheduling of emergency department services in metropolitan locations.

Efficient Patient Scheduling for Public Health Emergencies (EPS-PHE) using Multiagent Reinforcement Learning (MRL)

This approach seeks to maximize the benefits of space and time to make the most of PHE resource scheduling. Achieving timely transportation and effective resource allocation requires models for scheduling routes, emergency event availability points, event demand points, and significance. It is also necessary to use efficient DL-related optimization techniques. By using these algorithms, the allocation of resources may be done as quickly and efficiently as possible, guaranteeing that sources of emergency supplies can reach locations of need without delay.

The first stage involves executing the Q-value update process. Next, we present the rewarding process involving setting up DI and CI services. A Distributed Cost Function (DCF) uses an incremental Q-learning technique to improve each node's Q-values to boost the network's durability. Also, it introduces CI, a new kind of incentive system, which we'll talk about later. The DCF takes into account incentives from both nearby and faraway nodes.

The DI function integrates the residual energy and EPS efficiency between linking nodes to tackle EPS's key challenges. This enables the evaluation of the efficiency of the routing decision via the execution of logical actions. Furthermore, the insecure connection resulting from node displacement may lead to the transmission of information from the source. An acknowledgment (ACK) statement offers feedback on the incentive when an ACK message is compensated. The incentive is acquired by using information about the remaining energy and quality of the events. In all other instances, an unfavorable value will be given. The DI function is defined as:

$$DI = r_{t+1}\left(sta_{t+1}^{l}\right) = \begin{cases} L_{non-ACK}, & no\ acknowledgement \\ X_P.P + X_C.Cq, & with\ acknowledgement \end{cases} \quad (1)$$

where $P = \frac{P_{rem}}{P_{max}}$ (2)

$$Cq = CS(k,l) * \left(\frac{SS_q}{SS_{max}}\right) \quad (3)$$

The equation $r_{t+1}\left(sta_{t+1}^{l}\right)$ represents the instantaneous reward for node l in the future $(t+1)$. The absence of receiving an acknowledgment (ACK) for a sent message is denoted as $L_{non-ACK}$. The weighting factors X_P and X_C determine how much power-related and channel-related variables influence the reward calculation. P is the residual power P_{rem} of node l, normalized by the maximum power P_{max} that node l may possess. The channel quality factor, denoted as Cq, quantifies communication effectiveness between nodes k and l. The channel state between nodes k and l is denoted as $CS(k,l)$. The fraction of the sensed data that is sensitive to quality is denoted as SS_q. The highest value for the quality-sensitive component of the information is denoted as SS_{max}.

An MRL method often inhibits autonomous single-agent learning by facilitating data flows across nodes. Nevertheless, the restriction of only giving incentive feedback to agents with reciprocal communication still prevents information sharing among several agents. Practically, any action performed by agent k will inevitably alter the environment, affecting all nodes inside the system. The statement implies that how an activity is conducted has an immediate impact on the surrounding environment, and it is important for all nearby individuals to consider any feedback provided. Previous RL-based routing projects have not extensively studied the reward response mechanism in the broader intelligence context.

The results of these investigations corroborated the notion that the combination of DI and CI might enhance the efficacy of learning. Unlike classical EPS, which has a continuous state space, efforts have been made to provide CI or global usability tailored to each PHE application's unique characteristics. The proposed system incorporates a CI function that models the transmission channel of the information packet, specifically capturing the efficacy of the action conducted. The CI function is defined as follows:

$$CI = \begin{cases} 1, & message\ adjacent\ to\ sink\ node \\ -1, & otherwise \end{cases} \quad (4)$$

The distance between the previous and current nodes for reaching the destination influences the routing of communications in a network. It is important to note that there are two sides to this propagation direction—one next to the sink and the other more distant. If the distance between the current node and the sink is more than from the last step to the destination, transmitting the message toward nearby nodes is more beneficial. Positive incentive is used at this step to encourage the nodes. In contrast, a negative incentive penalizes nodes located at a greater distance.

2. Results and discussion

The RL step is conducted in a computer simulation, where the TensorFlow platform is employed in a cybernetic machine to design system-level software using the MRL route planning method. At the beginning of RL, the transport unit moves from the initial position towards the target point. Simultaneously, the DL algorithm inside the simulation continuously updates the current state of the whole milieu at each incremental step.

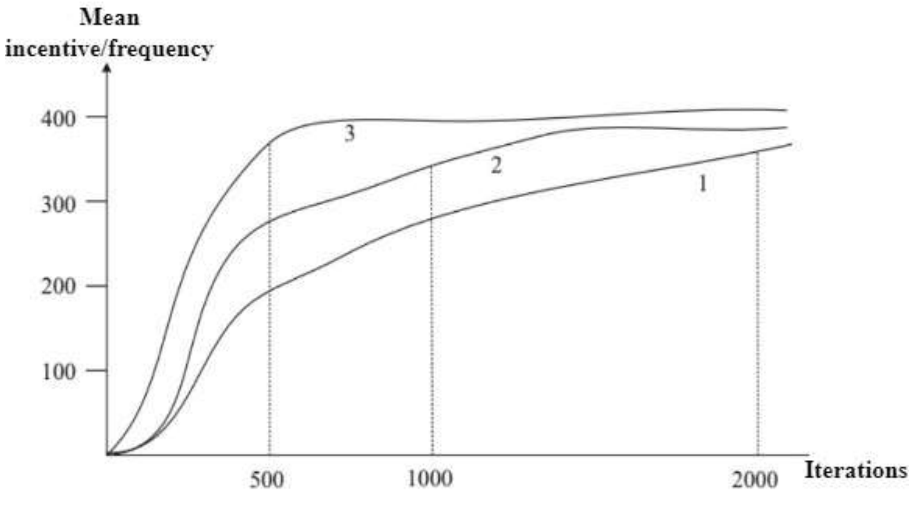

Fig. 1 Convergence rate versus number of iterations for EPS-PHE fram**ework**

Fig. 1 depicts the framework model consisting of PHEs of varying sizes and the convergence pattern illustrating the method of convergence of the RL testing. The X-axis reflects the number of PHEs, while the Y-axis represents the time taken for convergence of the entire algorithm. Curves 1, 2, and 3 depict the convergence function's tendency for various distribution PHEs, namely the convergence trend, while delivering 4, 40, and 400 PHEs, respectively. The reason for the suggested MRL method for EPS-PHE is that it involves a progressive learning process via continuous exploration of novel circumstances. When the magnitude of the setting remains constant, a smaller number of PHEs leads to a decreased likelihood of finding novel scenarios through arbitrary investigation.

Consequently, the system finds acquiring additional knowledge about the environmental state challenging. Conversely, as PHEs grow, the likelihood of facing dispersal units rises, enabling faster learning of various EPS states. This, in turn, significantly enhances the convergence rate. The convergence rate for model systems has been tested, showing that the EPS distribution system based on DL-MRL is feasible.

3. Conclusion and future scope

Multiagent Reinforcement Learning (MRL) shows an Efficient Patient Scheduling for Public Health Emergencies (EPS-PHE) method. At first, the system is meant to be a distributed multiagent system that can effectively solve the PHE and boost EPS. MRL has devised a way to use an autonomous reward system to measure the EPS-PHE input. As the name suggests, DI refers to the connections between people or information about two closely linked events. A CI checks how well the emergency network works or how well data is sent in EPS-PHE. The chance of finding distribution units increases as the number of PHEs increases. This makes it easier to understand the different EPS states. Because of this, the speed at which convergence happens is greatly increased. The model systems' convergence rate was checked, which showed that the EPS distribution system using DL-MRL was possible.

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