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ORIGINAL ARTICLE

A two-stage road traffic congestion prediction and resource dispatching toward a self-organizing traffic control system

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Abstract

Since decades, road traffic congestions have been recognized as an escalating problem in many metropolitan areas worldwide. In addition to causing substantial number of casualties and high pollution rates, these congestions are decelerating economic growth by reducing mobility of people and goods as well as increasing the loss of working hours and fuel consumption. In order to deal with this problem, extensive research works have successively focused on predicting road traffic jams and then predicting their propagations. In spite of their relevance, the proposed solutions to traffic jam propagation have been profoundly dependent on historical data. They have not also used their predictions to intelligently allocate traffic control resources accordingly. We, therefore, propose in this paper a new two-stage traffic resource dispatching solution which is ultimately aiming to implement a self-organizing traffic control system based on Internet of Things. Our solution uses in its first phase a Markov Random Field (MRF) to model and predict the spread of traffic congestions over a road network. According to the obtained predictions, the solution uses Markov Decision Process (MDP) to automatically allocate the road traffic resources. Our simulations are showing satisfactory results in terms of efficient intervention ratios compared to other solutions.

Keywords Markov random fields · Markov decision process · Road traffic congestion · Traffic congestion prediction

1 Introduction

Due to the rapidly growing urbanization as well as the tremendous expansion in transportation demands, we are witnessing increasing frequency and intensity of road traffic congestions worldwide. These congestions, which may basically result from various factors, including road capacity, driving behavior, and sporadic on-route events, are creating serious mobility problems and occasioning substantial number of casualties and financial losses [1]. Extensive research and development works (e.g., [2, 3]) have focused on the prediction of traffic jams in order to understand their causes, predict their occurrence, and plan actions accordingly. These plans are not always effective and optimized because of the characteristics of road traffic as well as the sporadic timings, locations, and intensities of traffic congestions. Consequently, lane blockages and vehicle queues could quickly spread to adjacent links and intersections while worsening the traffic conditions [4]. Predicting where observed congestions may spread over the transportation network is absolutely helpful for several parties, including traffic controllers (to balance the traffic flows in advance in the predicted congested areas/road segments), road users (to adapt their trajectories to avoid delayed commute times or to minimize exposure to CO_2 emissions), and police operators (to improve the efficiency of the deployment of their resources). Consequently, several transportation research efforts have moved their attention from predicting congestions to predicting the propagations of traffic congestions into space and time. To this end, several works have proposed solutions to predict congestion propagation speed (e.g., [5–8]), patterns (e.g., [9–11]), and effects (e.g., [12–14]). The proposed solutions present two

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main limits. First, most of them are data-driven. As they heavily rely on historical data, their time complexity does not basically allow them to be used to predict congestion propagations in large-scale transport networks. Consequently, most of them have been applied to small transportation networks consisting in few road segments. Second, to the best of our knowledge, none of the existing solutions has addressed the problem of using the predicted congestion propagations to implement intelligent solutions for traffic control. In fact, with the international economic crisis, several police departments are operating with limited resources, which negatively impacts personnel's workload balance and service quality. Efficient use of these limited resources is, more than ever, a fundamental requirement. One intuitive way is to [re] allocate police resources where incidents are predicted to happen, according to a proactive and predictive policing strategy. While most of the existing works deal with resource allocation and incident prediction separately, some efforts have attempted to combine both of them in the context of criminal incidents [15, 16], but, to the best of our knowledge, nothing has been proposed for traffic congestion propagation.

To address these limits, we propose in this paper a new traffic regulation resource allocation scheme which is ultimately designed to create a self-organizing traffic control system. The proposed scheme is based on two stages. The first stage uses a Markov Random Field (MRF) to model and predict the propagation of non-recurrent traffic congestions over a road network. The second stage consists in automatically updating the deployment of the traffic regulation resources (e.g., police patrols, drones) in accordance with the predicted congestion propagation using a Markov Decision Process (MDP). The objective is to provide an efficient traffic regulation resource allocation scheme in order to maximize the utility of the deployed resources over a long-time horizon.

Our contributions are summarized as follows: (1) A new model for predicting traffic congestion propagation using a Markov Random Field (MRF). In contrast with data-driven models, our model does not require intensive historical traffic data and can, therefore, be suitable to predict traffic congestion propagations at city-level road networks and (2) a two-stage resource allocation-reallocation scheme used to implement a self-organizing traffic control system based on Markov Decision Processes (MDP).

In the remainder of this paper, Section 2 outlines the state of the art on emergency vehicle allocation in general and traffic resource [re] allocation in particular, as well as on traffic congestion prediction. Section 3 describes our two-stage traffic resource allocation-reallocation scheme. It particularly focuses on our traffic state estimation model as well as on our self-adaptive resource allocation solution. Section 4 presents the performance analysis of our solution. Section 5 concludes the paper and highlights our future works.

2 Related work

The main objective of our work is to propose a model that allows to dynamically reallocate traffic resources in a way to deploy them in places where traffic congestions are predicted to propagate in an urban transportation network. Therefore, our work joins two problems, traditionally addressed separately in the literature: (1) traffic resource allocation and (2) traffic congestion propagation prediction. In the following, we present a general overview of the relevant works in the state of the art of the two problems.

2.1 Emergency resource allocation

The problem of optimally placing responders in space to respond to incidents has been well explored in the literature under the generic name of Emergency Vehicles (EVs) allocation problem (ambulances, fire engines, police patrols, etc.) [17]. In this problem, three main decisions need to be made: (1) where EVs should be located such that when requests are received, they are answered in a time-efficient way? (allocation problem), (2) which available EV should be assigned and sent to every request's site? (dispatching problem), and (3) once an incident is answered, shall the newly available EV be sent to its original location or to a different one? (reallocation problem). Among all the EV types, Emergency Medical Vehicles (EMVs) have attracted most of the research works. In general, it is assumed that EMVs are assigned to depots. Because time is very critical in emergency situations, these depots should be located in a way to ensure an adequate coverage and rapid answer time. A service request is said to be covered if it is responded within standard time-frames [18]. Many countries have standards in this regard, like in the USA where 95% of requests should be served within 10 min in urban areas and 30 min in rural areas [19]. Consequently, EMV depots' allocation and reallocation problem has been attracting substantial research work, especially in operational research [20, 21]. Mathematical proposed models are grouped into two main categories: static and dynamic [22]. In static models, the locations of EMVs (depots) are decided at the beginning of a planning horizon and do not change for that horizon. In every depot, available ambulances are dispatched upon service requests (incidents) and are traditionally assumed to return to their original depot once they finish their services. Dynamic models implement a redeployment strategy, where idle and newly available ambulances are dynamically reallocated, either at the end of some planning horizon or in real-time manner to increase service coverage [18, 23]. More detailed reviews about the topic could be found in [22, 24].

The problem of police resource allocation-reallocation shares common characteristics with the problem of EMV allocation-reallocation, and several models proposed for the latter are also applied for the former. Indeed, police force planning has been widely analyzed as a maximum covering location problem (MCLP), which seeks to locate a fixed number of facilities such that the number of demand nodes that can be covered in pre-specified time limit (or service distance) is maximized [25, 26]. The model and its variations have been mainly used for the creation of optimal police patrol static areas [27, 28]. In addition, police dispatching systems are based on general emergency vehicle dispatching models [29–31], and commonly follow a shortest-path vehicle's dispatching approach [32] which is implemented based on a routing algorithm that determines the quickest/shortest route from a response unit to an incident [33]. The recent work in [31] proposed a new police dispatching system that combines availability of units, predicted response time, officers' driving qualifications, and service coverage.

While several EMV models are also applicable for police resources' allocation-reallocation, there is an important difference between operations of police patrols and ambulances. Mainly, ambulances only follow an incident-response dispatching mode, but police patrols, in addition to the incident-response mode, regularly perform street patrolling to maintain a visibility and presence that act as deterrence, either to reduce crimes or to enforce traffic laws [20, 26, 34]. Consequently, several efforts have addressed the problem of police patrols routing (or patrolling), with the aim of selecting the best routes and locations to visit in order to minimize incidents' expected response time [35–37]. The proposed models focus mainly on the context of crime incidents, and strategies include allocating patrols based on forecasted crimes [15, 16, 35] (where and when crimes are expected to happen) and crime hot-spots [31, 34, 38] (places with historical high crime rates).

Furthermore, the topic of resource reallocation for road traffic management has been addressed by few research works, aiming at maximizing spatial traffic incident coverage [39] and maximizing response time [40, 41]. One of the most relevant efforts for our work is the model proposed in [26] for traffic police routine patrol vehicle (RPV) on interurban road network. RPVs need to be reallocated dynamically on both hazardous sections and on roads with heavy traffic in order to increase police presence, in an attempt to prevent or reduce traffic accidents and congestions through deterrence and enforcement. The authors combined incident-response dispatching systems from depots, similar to that of ambulances, with location choices over a road network in order to detect and prevent offenses and respond to incidents in a timely manner. The authors proposed mathematical formulations of different reallocation scenarios based on operational research and traffic enforcement. Another relevant work is proposed in [42] and addressed the problem of computing randomized traffic police patrol strategies in order to avoid predictability and provide adequate coverage of different areas of a city in Singapore, and this is to persuade drivers to comply with traffic laws. Authors modeled the problem as a Stackelberg game with one defender (the police) and multiple adversaries (drivers) [42].

To the best of our knowledge, none of the existing traffic incidents' resource reallocation approaches considers the idea of reallocating resources in places where traffic congestions are predicted to propagate.

2.2 Prediction of traffic congestion propagation

In order to understand the propagation of congestion, several traffic flow simulations and models have been suggested (e.g., [43, 44]). For more realistic support to these simulations and models, some empirical studies have addressed the transition mechanisms and the transition points during the creation and propagation of traffic jams [45, 46]. In this regard, some empirical studies have analyzed the velocity on highways as well as the spatiotemporal statistics of density and have concluded that traffic jams move along a lane while maintaining a nearly standing structure [5, 6]. Other studies have analyzed the spatial patterns of traffic jams and found that long-range relationship features of traffic jams are weakened slowly with distance [23].

Furthermore, Nguyen et al. [11] have addressed the causal interactions among historical traffic congestions. To this end, the authors have presented STCTree (a Dynamic Bayesian Network-based algorithm) which builds causality trees based on spatial and temporal information related to traffic jams in road segments. Recurrent sub-trees are then determined and used to find out interaction patterns among spatiotemporal congestions. Zhao et al. [7] have proposed a cascading overload failures approach to study the propagation of traffic jams. The authors have found that this propagation has a relatively constant speed. Jiang et al. [9] have used empirical traffic data in big cities to study the behavior of the spatiotemporal propagation of traffic jams. The authors have found that jams propagate radially from multiple jam centers with a range of velocities. Fei et al. [8] have proposed a practical approach to estimate the propagation speed of traffic congestions and predict their boundaries accordingly. To this end, the authors have used a Van Aerde single-regime flow model and the kinematic wave theory to make predictions for a single congestion given an observed traffic incident. Liu et al. [12] have presented a dynamic spatiotemporal model based on a physical traffic shockwave model and GIS road network to analyze and predict the propagation patterns and the influence of road incidents in straight roads as well as in road networks. Li et al. [4] have proposed an improved cellular automata model to simulate traffic congestion propagation resulting from the occurrence of a traffic accident on a basic link. Ma et al. [47] have analyzed the traffic congestion propagation using a combination of road enclosure, plume model, and spherical extrapolation methods. Pan et al. [13] have used incident data and traffic data datasets to classify historical incidents based on their features (e.g., time, location, type of incident). The authors have also modeled the impact of these incidents as quantitative time varying spatial spans. These spans have then been used to predict and quantify the impact of real-time incidents. In a recent work, Xiong et al. [10] have predicted the footprint of congestion propagation patterns as Propagation Graphs (Pro-Graphs). The root of each Pro-Graph is defined as a set of jammed roads spreading congestion to nearby roads. The authors have also proposed a brute-force Propagation Probability Index algorithm (PPI_Fast) and experimented it on real-world dataset from Shenzhen (China). Finally, Wang et al. [14] have developed an integer programming model to estimate the spatiotemporal impact of road incidents. The authors have used a set of constraints to ensure consistency between the shape of the congested region in the speed map and the propagation of shockwaves. The proposed model uses information about a given incident (location and starting time) as well as historical speed data and outputs the spatiotemporal region affected by this incident.

To conclude this section, our state of the art showed that the problem of traffic resource allocation-reallocation and the problem of traffic congestion propagation prediction have been studied separately and have not been integrated in the same model yet. We believe that their integration allows for a better management of traffic resources. In the following sections, we propose a model for such integration and we analyze its performance through a series of simulation experiences.

3 Two-stage resource allocation strategy

In this section, we outline a two-stage traffic resource allocation scheme. This scheme includes two main components: (1) A traffic state estimation model and (2) a self-adaptive resource allocation solution.

3.1 Traffic incident repercussion prediction

In this section, we present a Markov Random Field (MRF) to model the propagation of traffic congestions over the road network. The proposed model relies on the underlying dependencies between road junctions (or intersections). We assume that the road network is undirected (i.e., double-lane roads). An example of MRF is presented in Fig. 1. The MRF corresponds to a small-scale road network with five road segments and five junctions. The junction in which a congestion event has occurred is highlighted in red, three susceptible junctions of congestion are highlighted in orange, and the free flow junction is highlighted in green.

A road junction is defined as a geographical point where two or more road segments intersect. It might correspond to an intersection between two distinct roadways or to a liaison point between two segments belonging to the same road way.

The main difference between MRF and Bayesian networks is that the former allows for cyclic dependency modeling

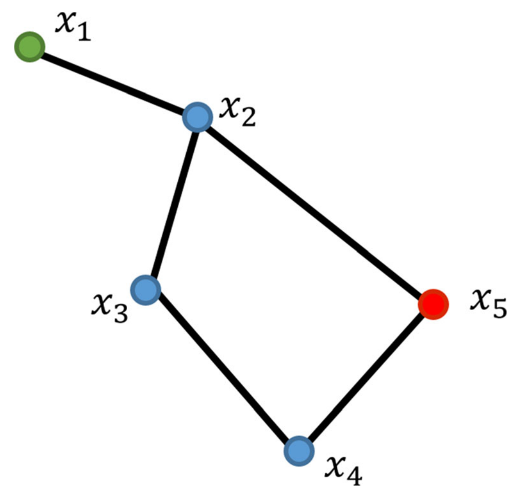

Fig. 1 An example of MRF corresponding to a small-scale road network

which might occur in the road congestion context. Therefore, one could easily model the cyclic propagation of gridlocks over a road network. For example, in Fig. 1, if a congestion occurs at location x_5, then, after the incident has been dealt with and tailback has been mitigated, the congestion might propagate across locations x_2, x_3, and x_4 and returns to x_5.

Formally, an MRF is defined as follows:

Given an undirected graph $G = (S, A)$, the set of random variables $X = \{X_s, s \in S\}$ is a MRF with respect to G if the following properties are satisfied:

(i) If X_s and X_t are two non-adjacent variables, then they are independent conditionally given all other variables.
(ii) A random variable X_s is conditionally independent of all other variables given its neighbors.
(iii) Let $\mathcal{A}_S$ and $\mathcal{B}_S$ be two subsets of variables. $\mathcal{A}_S$ and $\mathcal{B}_S$ are conditionally independent given any disjoint subset $\mathcal{C}_S$.

The definition of the MRF relies on the definition of the joint density probability $\Pr(X = x)$. This probability cannot always be established unless a factorization method is implemented. The most common factorization method is called the clique. A clique C is a subset of S such that every two vertices in C are adjacent.

$\{X_s, s \in S\}$ is considered as a MRF with respect to G if $Pr(X = x) = \prod_{C \in Cliques(G)} \phi_C(x_C)$.

Markov Random Fields have been extensively used in several applications where the spatial component is intrinsically part of the problem definition. It has been used in the context of unsupervised image segmentation [48], malware propagation modeling [49], spatio-temporal evolution of microstructures [50], etc. Due to its ability to model spatial correlation, MRF can be used to model the propagation of traffic congestion which can be perceived as a result of direct connections between road junctions.

In the context of traffic congestion propagation modeling, the road network is assimilated to a complete graph in which the junctions (or intersections) are represented by the graph vertices and the road segments by the arcs.

The monitored area consists of a finite set of sites corresponding to the road junctions $S = \{s_i, 1 \le i \le N\}$. Let us denote by Ω the state space corresponding to the possible traffic states. For the sake of simplification and without loss of generality, let us assume that $\Omega = \{\omega_c, \omega_f\}$. ω_c (resp. ω_f) corresponds to the congested traffic (respectively free flow traffic). We denote by X_i the random variable taking its value in Ω and corresponding to the traffic state at the junction S_i. We define the MRF as the collection $X = \{X_i, 1 \le i \le N\}$ with respect to the state space Ω. The MRF model relies on a neighborhood system on S (denoted by $\mathcal{N}$) and defined as a family of subsets of S: $\mathcal{N} = \{\mathcal{N}_i, 1 \le i \le N\}$ such that each $s_i \in S$, $s_i \notin \mathcal{N}$ and a site s_j belongs to $\mathcal{N}_i$ if and only if $s_i \in \mathcal{N}_j$.

The MRF relies on the following assumption:

$$P\left(X_i = x_i | X_j = x_j, s_i \neq s_j\right) = P\left(X_i = x_i | X_j = x_j, s_j \in \mathcal{N}_i\right)$$

The random field is called a Gibbs random field (GRF) if: $P(X = x) = \frac{1}{\sum_{x \in \Omega^N} e^{\frac{-U(x)}{T}}} e^{\frac{-U(x)}{T}}$, where T is the so called "temperature" of the system and $U(x)$ is called the potential function or the energy corresponding to the configuration x.The potential function consists in the sum of clique potentials:

$$U(x) = \sum_c \phi_i(x)$$

We consider the propagation of traffic congestion across a set of linked N road junctions. Each junction corresponds to a site of a MRF and can be at one of the two states: congested (C) and free flow (F).

We address the interaction between C-F pairs of junctions in order to model the propagation of congestion. The evolution of congestion is driven by the direct interactions between C-F pairs in the road network. These interactions essentially represent the impact of a congested node on its immediate neighbor nodes. For instance, if two nodes x_i and x_{i+1} are two adjacent nodes such that x_i is jammed and x_{i+1} is free-flowing, then the possible scenarios could be either x_{i+1} will become jammed as the congestion propagated from x_i or not if the required resources have been dispatched on the right time or if the bottleneck is only located at x_{i+1}. The interaction between C-F nodes depends also on the direction of the traffic. If the traffic is directed from x_{i+1} to x_i, then x_{i+1} is likely to be jammed when a bottleneck occurs in x_i. The interactions between both congested sites (C-C) are not considered in this work. Such interactions represent the negative impact a congested node might have on an adjacent jammed node: whether it will worsen the traffic state in the considered nodes or not.

We assume that at given time t, a traffic incident occurs in a junction i resulting in a traffic jam. Due to the immediate interaction between the aforementioned junction and its immediate neighbors, and depending on the traffic direction, the congestion is likely to propagate to the road segments in the neighborhood. Two approaches can be considered at this level (depending on whether we treat identically or not the junction having initiated the congestion and the neighbor junctions to which the congestion has propagated). For instance, if a road accident occurred in one junction and resulted in a traffic congestion, then this junction will require more resources than its neighbor junctions to alleviate the traffic.

To model the C-F interactions, it is crucial to define an appropriate potential function.

With respect to the defined MRF, we consider a two-site clique and we define the following potential function:

$$\phi_i(x) = \phi_i(x_i) = -A \sum_j \sigma_i \sigma_j, \forall s_j \in \mathcal{N}_i, \quad A > 0,$$

where A is a constant scaling factor used to adjust the sensitivity of the model. The functions σ_i and σ_j are bijective functions of x_i and x_j respectively. We set:

$$\sigma_i(x) = \sigma_i(x_i) = x_i$$

Whence, the cumulative potential function is:

$$U(x) = -B \sum_{i,j} \sigma_i(x_i) \sigma_j\left(x_j\right), B > 0$$

where $B = n_c A$ is a positive constant.

We propose a simulated annealing (SA) method to evaluate the evolution of the propagation of traffic incidents' repercussion within the neighborhood system. The overall objective being to use the minimum energy to bring the system to a steady-state.

The SA method runs as follows:

(i) Random node sites (road junctions) are visited once (sweep).
(ii) The state of each site is updated according to the states of its neighbors in the clique and to the considered potential function.
(iii) The process is repeated for a finite number of sweeps (n) and using a temperature function $T(n)$.

The SA method proceeds through several steps of temperature reduction exploring a range of configurations close enough to the global optimum. Afterwards, the algorithm converges toward low-energy regions before reaching a global minimum.

In each sweep, a decision is made at each node whether the state changes or remains unchanged in Ω. The potential function at each site $\phi_i\left(x_i^{\omega}\right)$ is approximated by $\hat{\phi}_i\left(x_i^{\omega}\right) = \left\{x_i = \omega | x_{i'}, i' \in \mathcal{N}_i\right\}$ and depends on the states of the site i and the sites in the neighborhood $\mathcal{N}_i$.

Using this SA model, the probability of changing the state of a given node i is:

$$\Pr(X_i = \omega) = \frac{e^{-\frac{\phi_i\left(x_i^{\omega}\right)}{T(n)}}}{\sum_{\omega' \in \Omega} e^{-\frac{\phi_i\left(x_i^{\omega'}\right)}{T(n)}}} \tag{1}$$

Which means that the next traffic state at site i will become $\omega \in \{\omega_c, \omega_f\}$.

This expression can be simplified in the case of two traffic states:

$$\Pr(X_i = \omega) = \frac{1}{1 + e^{-\frac{\phi_i\left(x_i^{\omega'}\right) - \phi_i\left(x_i^{\omega}\right)}{T(n)}}} \tag{2}$$

where $\omega \neq \omega'$.

For the sake of simplification, let us set $\omega_c = 1$ and $\omega_f = 0$. Therefore, the potential functions can be written as follows:

$$\phi_i\left(x_i^0\right) = -A \sum_{j \in \mathcal{N}_i} \sigma_i \sigma_j = -A \sum_{j \in \mathcal{N}_i} x_i x_j = 0$$

and similarly:

$$\phi_i\left(x_i^1\right) = -A \sum_{j \in \mathcal{N}_i} \sigma_i \sigma_j = -A \sum_{j \in \mathcal{N}_i} x_i x_j = -A \sum_{j \in \mathcal{N}_i} x_j$$

Whence, the probabilities in Eqs. (1) and (2) become:

$$\Pr(x_i = 1) = \frac{1}{1 + e^{-A\frac{\sum_{j \in \mathcal{N}_i} x_j}{T(n)}}}$$

and

$$\Pr(x_i = 0) = \frac{1}{1 + e^{A\frac{\sum_{j \in \mathcal{N}_i} x_j}{T(n)}}}$$

In the literature dealing with SA and its applications [48, 51, 52], the annealing scheme relies on the temperature function $T(n) = \frac{c_0}{\log n}$ in which c_0 is a constant that impacts the convergence and accuracy of the SA scheme.

3.2 A Markov decision process model for optimal resource dispatching

In this section, we present a Markov decision process (MDP) for the optimal allocation/reallocation of traffic regulation resources. The objective is to provide an efficient resource allocation/reallocation scheme in response to predicted traffic states in order to maximize the utility of the deployed resources over a long-time horizon.

The proposed MDP model relies on the following parameters:

- d: number of congested junctions
- m: total number of resources.
- $\Pr(x_i = 1)$: the priority level of the junction i.
- $\eta_{k,\ i}$: The utility gained by the resource a_k after being dispatched to the junction i.
- $\tau_{k,\ i}$: the travel time required by the resource a_k to reach the junction i.

An MDP is defined as a tuple (S, A, P_a, R_a) where:

- S is a finite set of states.
- A is a finite set of actions. A_s is the set of available actions when the system is at state s.
- P_a, called the transition probability system, is defined as follows:
  $P_a(s, s') = \Pr(s_{t+1} = s' | s_t = s,\ a_t = a)$. It corresponds to the probability that the system went from state s to s' using the action a
- $R_a(s, s')$ is the reward gained when the system state transitions from state s to s' using the action a.

The associated goal is to find a so-called "policy" denoted by π. $\pi(s)$ corresponds to the action that should be taken when the system is in state s. Once a policy is determined, the MDP is equivalent to a classical Markov chain and $P_a(s, s') = \Pr(s_{t+1} = s' | s_t = s)$. The choice of the policy π relies on the definition of a "cost" function that has to be optimized and which consists generally in the cumulative function of rewards.

$$\lim_{T \to \infty} \sum_{t=0}^{T} \gamma^t R_{\pi(s_t)}\ (s_t, s_{t+1})$$

where γ is a discount factor such that $0 \leq \gamma < 1$. It is used to ensure that the cumulative function remains finite, which provides a convergence for the policy-finding algorithm.

Finally, an optimal policy denoted by π^* is given by:

$$\pi^* = \arg\max_{\pi} \lim_{T \to \infty} \sum_{t=0}^{T} \gamma^t R_{\pi(s_t)}\ (s_t, s_{t+1})$$

3.3 States

Let us denote by s_t the state of the system at time t. s_t is the vector $\left(\sigma_t^1, \sigma_t^2, \ldots, \sigma_t^{N_A}\right)$, where σ_t^k is the state of the resource k at time t.

$$\sigma_t^i = \begin{cases} k, \text{if the resource } R_i \text{ is} \\ \text{dispatched to the site } k \text{ at time } t \\ 0, \text{if the resource } R_i \text{ is idle at time } t \end{cases}$$

The state space is defined by $\Sigma = \{\sigma | \sigma \in \{0, \ \ldots, d\}^m\}$.

3.4 Example

Let us consider the example illustrated in Fig. 2. Four resources $R_{i,\ 1\leq i\leq 4}$ are located in eight different intersections. $\sigma_t = (0, 0, 5, 6)$ if at time t, resource 1 and 2 are idle while 3 and 4 are deployed in intersections 5 and 6, respectively.

3.5 Action space

The decisions in our model represent the choice of which resource should be reallocated in response to a traffic event predicted in a given road junction. When the system is at a state s_t, the set of actions $A(s_t)$ corresponds to the reallocation scheme. Depending on whether a resource k is already allocated or not to an intersection, its state is either changed to 0 (if it becomes free) or i if it has been allocated to the intersection. We assume that the reallocation of a resource is restricted to its current site i or to the adjacent sites $\mathcal{N}_i$ only. In the example depicted in Fig. 2, the resource R_2 can be reallocated to intersection 5 resulting in an action set $A(\sigma_t) = \{5\}$.

3.6 Rewards

The reward is a function of the probability of the event occurrence and the cost of resource migration. Therefore, the gained reward depends on the location of the event as well as the originating location of the reallocated resource.

The gained utility depends on two main factors:

– The location of the intersection: the farther the intersection is from the current location of the reallocated resource, the higher will be the cost of its deployment and the risk of reaching the congested area after the incident has already occurred.

– The probability of traffic incident in the concerned junction. In fact, when a resource is assigned to the designated intersection, the traffic event that was predicted might be a false alarm and therefore other intersections that require real intervention might be disregarded.

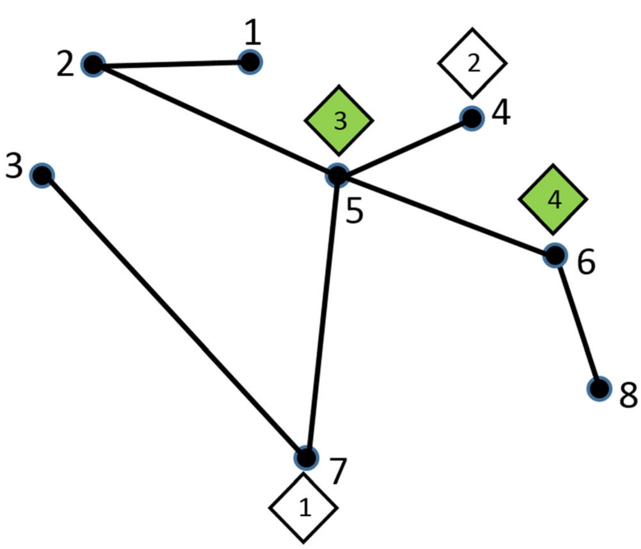

Fig. 2 An example of system state with eight intersections and four resources. The state of the system is (0,0,5,6) since resources (represented by diamonds) 1 and 2 are available (0) while resources 3 and 4 are dispatched to intersections 5 and 6, respectively

The utility function $\eta^{\omega}_{k,\ i}$ corresponds to the redeployment of a resource k to an intersection i for with the state ω.

In order to achieve the model's overall objective which consists in minimizing the costs of alleviating the impacts of traffic incidents, we define the following reward function:

$$\eta^{\omega}{}_{k,i} = \sum_{i=1}^{n} f(i)/\left(c_i^k\right)$$

where $f(i) = \begin{cases} \Pr(X_i = \omega_c)\text{if a resource is redeployed to intersection } i \\ 0, \text{otherwise} \end{cases}$

and c_i^k is the cost of deploying the resource k to the intersection i.

Since the cost of resource deployment intrinsically depends on the spatial location of both resources and incidents, we use the travel time $\tau_{k,\ i}$ as a cost function.

3.7 Transitions

The transitions in the proposed MDP model are triggered when a traffic incident occurs. In such a case, the MDP carries out the implemented policy and decides which state shall be the next based on the transition probability $P_a(s, s')$.

Based on the Accelerated Failure Time (AFT) model [53], we model the elapsed time t between two successive incidents by the density function $f(t|\,w)$, where t follows an exponential distribution and w is a set of arbitrary features that impact t. The arrival rate is modeled by an exponential distribution as a log-linear model in terms of the features w. Hence, the probability distribution of time to next incident in a given intersection is:

$$f(t|w) = \lambda e^{-\lambda t}$$

The computation of the parameter λ is achieved using the historical data:

(i) When the system is at a state s_t, an action $a \in A(s_t)$ is taken
(ii) The system obtains a reward $r(s_t, a)$
(iii) The system takes time δt to carry out the transition

3.8 Optimal policy and reinforcement learning

In order to determine an optimal policy π^*,we define a value function $V^{\pi} : S \to \mathbb{R}$ to calculate the expected sum of discounted rewards obtained with respect to the policy π:

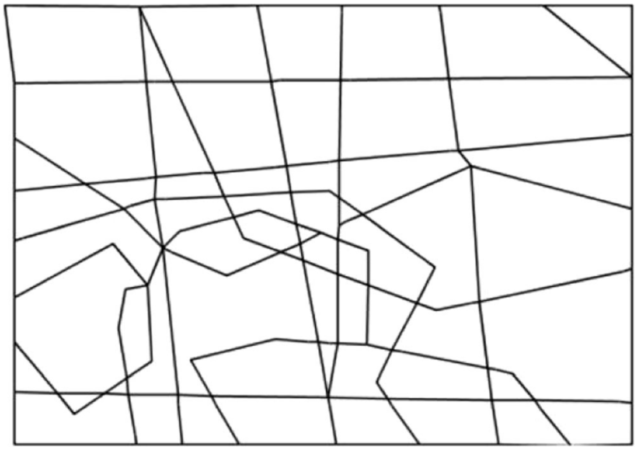

Fig. 3 Road network of the considered area

$$V^{\pi}(s) = \sum_{s'} P_{\pi(s)}\left(s, s'\right)\left[R_{\pi(s)}\left(s, s'\right) + \gamma V\left(s'\right)\right]$$

Using the policy iteration algorithm [50], we compute the optimal policy π^*. The algorithm runs as follows:

(i) Initialize a policy π^0 randomly
(ii) At each iteration q, compute the value of policy π^q
(iii) Update the policy π^q such that

$$\pi^{q+1} = \arg\max_a \sum_{s'} P_{\pi(s)}\left(s, s'\right) V^{\pi^q}\left(s'\right)$$

(iv) If $\pi^q \neq \pi^{q+1}$, go to step (ii)

Since the transition probabilities and the rewards are not known, we recourse to a reinforcement learning strategy. We define the following action-value function:

$$Q^{\pi}(s, a) = \sum_{s'} P_a\left(s, s'\right)\left[R_a\left(s, s'\right) + \gamma V^{\pi}\left(s'\right)\right]$$

This action value function represents the expected value of cumulative random rewards obtained when the decision taken while in state s is the action a before following the policy π.

In order to optimize Q^{π}, we adopt a Q-learning scheme [47]. The Q-learning algorithm aims at maximizing the cumulative reward starting from the current state s. First, Q is initialized to an arbitrary value. Then, in each iteration at time t, an action a_t is selected to get a reward r_t before transitioning into a state s_{t+1} and Q is updated. This process is achieved using the following expression:

$$Q^{t+1}\left(s_{t,}, a_t\right) = (1-\alpha) Q^t\left(s_{t,}, a_t\right) + \alpha\left[r_t + \gamma \max_a Q^t\left(s_{t+1,}, a\right)\right]$$

where α is a constant $0 \leq \alpha \leq 1$ called learning rate.

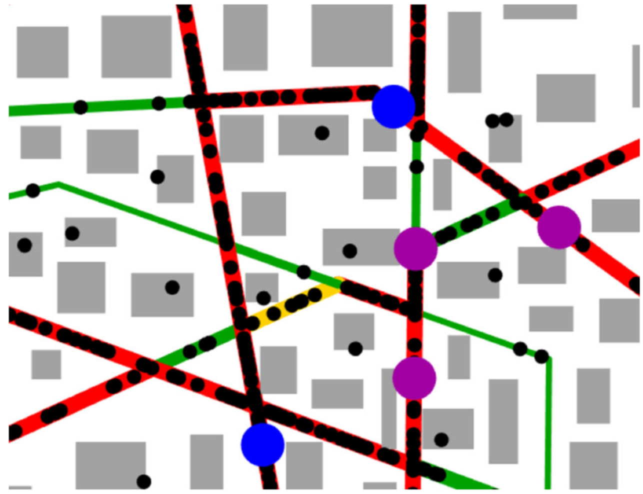

Fig. 4 Congested road segments (red), predicted congestion (yellow) and free flow road segments (green). Resources are represented with blue (resp. purple) disks for random (resp. MRF-MDP) scheme dispatching

4 Performance analysis

This section is devoted to the performance assessment of the proposed resource reallocation scheme. The experiments were conducted using the GAMA platform.[1] We considered a road network in the city of Manhattan with a population of $D = 10{,}000$ (Fig. 3). The total number of road junctions in the considered area is 217.

We assumed that the population corresponds to the number of vehicles. The simulation (Fig. 4) was performed for a week during the day and we considered only one regular activity pattern: home–work–home. The working times were set between 8:00 am and 6:00 pm and we considered the traffic induced by the mobility of the population. In order to represent a tailback phenomenon, we set a threshold for road capacity that when exceeded, corresponds to a traffic congestion. The capacity of a road segment has been calculated using the following formula:

$$C = \frac{L}{\lambda},$$

where L is the length of the road segment and λ is the average length of a vehicle (in this experiment we considered an average length of a sedan car $\lambda = 4.5$ m).

In the first experiment, we evaluated the accuracy of the congestion propagation prediction algorithm. We varied the population size between 5000 and 10,000 and we calculated the following ratio:

$$r = \frac{|E-A|}{A}$$

where E is the number of estimated congested junctions and E is the number of actually jammed congestions. Table 1 reports

[1] https://gama-platform.github.io/

Table 1 Accuracy of MRF-based congestion propagation algorithm

D	5000	6000	7000	8000	9000	10,000
r	82.3%	81.8%	84.7%	84.5%	86.8%	88.5%

the results of this experiment in which the proposed MRF algorithm has shown satisfactory results (82% for $D = 5000$ and 88.5% for $D = 10{,}000$).

In the second series of experiments, we aimed at studying the impact of the proposed model on the responsiveness of the reallocated patrols. The performance indicator that has been considered in this experiment is determined based on the time congestions last before a patrol arrives at the jammed site.

Formally, this performance indicator denoted ρ is defined as follows:

$\rho = \frac{1}{N}\sum_{i=1}^{N}\sigma(i)$, where N is the total number of intersections and $\sigma(i)$ is defined as follows:

$\sigma(i) = \frac{\tau_p}{\tau_c}$, where τ_p (resp. τ_c) is the time a junction is congested with a patrol on-site (resp. total congestion time).

We consider a number η of patrols that are initially deployed at random intersections and we vary η between 10 and 100. The goal of this experiment is to determine whether the number of patrols impacts the effectiveness of the proposed scheme. Table 2 reports the results of this experiment considering three reallocation schemes: (1) our proposed MFR-MDP scheme, (2) random reallocation scheme, and (3) on-demand scheme in which patrols are only reallocated to intersections once they are congested (post-congestion reallocation). We noticed that the higher the number of patrols, the higher the performance of our approach albeit when the number of patrols is too large the classical schemes (random and on demand) and the proposed one are quite close in terms of responsiveness. For the considered population, the number of patrols for which our strategy outperforms the classical ones is approximately 50 patrols.

We also studied the impact of the population size and consequently the frequency of congestions. Table 3 reports the results of this experiment showing the evolution of the number of congestions as well as the percentage of efficient intervention

Table 3 Impact of the population size on the performance of the MRF-MDP scheme using 50 patrols against classical approaches

D	500	1000	2000	5000	7000	10,000
Incidents	113	194	308	722	894	1033
$\rho_{MRF-MDP}$	0.37	0.42	0.47	0.54	0.58	0.62
ρ_{RAND}	0.33	0.39	0.42	0.44	0.44	0.57
$\rho_{OnDemand}$	0.35	0.4	0.41	0.47	0.52	0.6

according to the population size. As the population size increases, the number of gridlocks rises. Besides, we noticed that the proposed approach outperforms the classical ones for large population size.

Moreover, we investigated the efficiency of the proposed approach by assessing the number of interventions per patrol during the simulation. Table 4 reports the results of this experiment and details the average idle time that police patrols stall in their initial intersections or on their route to the allocated intersections.

This experiment has shown that one strength of the proposed solution is that it minimizes the idle time: for example, the average idle time of 50 patrols using the MRF-MDP strategy is very close to the one recorded for 100 patrols using the random allocation strategy and for 80 patrols when the on-demand strategy is implemented. Intuitively, one could explain the result by the fact that when the on-demand strategy is adopted, it might happen that a patrol reaches the allocated site after the traffic congestion has been mitigated.

We have also studied in this experiment the frequency of estimating the congestions and their propagation. For a population of 10,000 vehicles and 50 patrols, we varied the interval of time to update the traffic state estimation as well as the relocation of patrols. Figure 5 depicts the results of this experiment: for time intervals less than 15 min, the MRF-DP strategy yields a low rate of effective interventions and is close to the random scheme while for large time intervals exceeding 45 min, the MRF-MDP is close to the on-demand strategy.

We also studied the impact of the number of sweeps (n) on the performance of the MRF model. Fig. 5 depicts the results of the experiment consisting in varying the number of sweeps between 10 and 100. Unsurprisingly, we noticed that up to n_s=40, the higher the number of sweeps, the higher is the ratio of effective resource reallocation. However, the running time until the estimation algorithm converges steeply increases

Table 2 Performance of the MRF-MDP approach according to the number of reallocated patrols

η	10	20	50	80	100
$\rho_{MRF-MDP}$	0.18	0.35	0.62	0.66	0.72
ρ_{RAND}	0.2	0.40	0.49	0.51	0.47
$\rho_{OnDemand}$	0.11	0.28	0.33	0.55	0.61

Table 4 Recorded idle time for police patrols (1.0 is 1% of idle time)

η	10	20	50	80	100
MRF-MDP	79.6	66.4	37.3	29.7	17.6
Random	75.8	72.8	59.6	44.8	38.8
On-demand	66.6	58.8	51.2	39.4	32.8

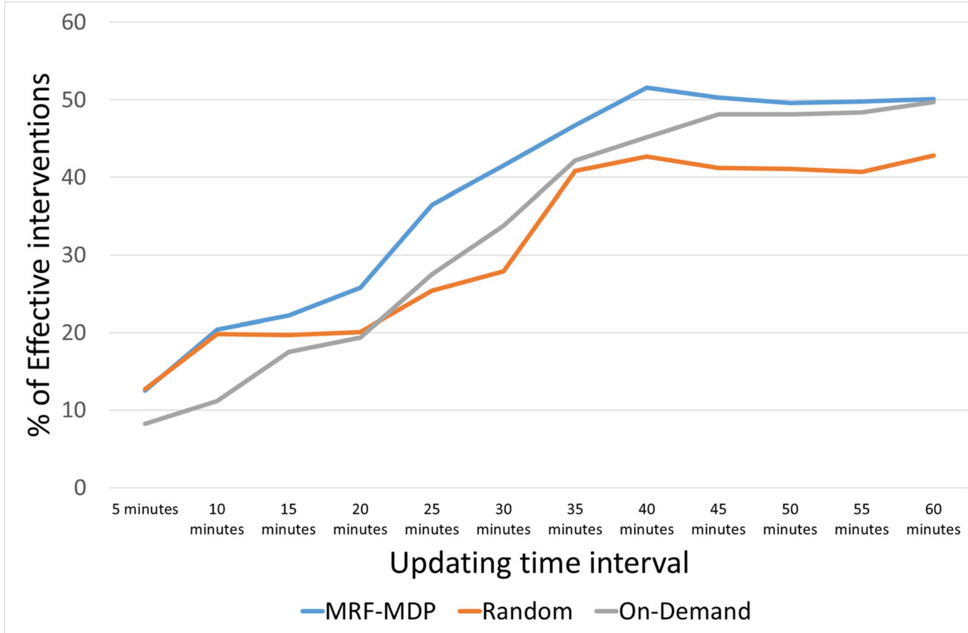

Fig. 5 Percentage of effective patrol interventions for different updating time intervals

when n_s is greater than 40. Therefore, the response time for reallocation decision is compromised, which impacts the effectiveness of the model (Fig. 6).

5 Conclusion

In this paper, we addressed the increasingly complex problem of predicting road traffic congestions. In contrast with existing works, our solution is not data-driven. As such, it can be deployed on large-scale road networks. In addition, our solution is using the predictions that we model and generate via a Markov Random Field (MRF) to judiciously reallocate traffic control resources based on a Markov Decision Process (MDP). Our simulations are reflecting that our solution outperforms random reallocation and post-congestion intervention approaches. In order to improve our performance, our future works will focus on implementing additional resource reallocation mechanisms. We will also implement a machine learning module that will be deciding on the right resource reallocation mechanisms to deploy depending on current contextual information.

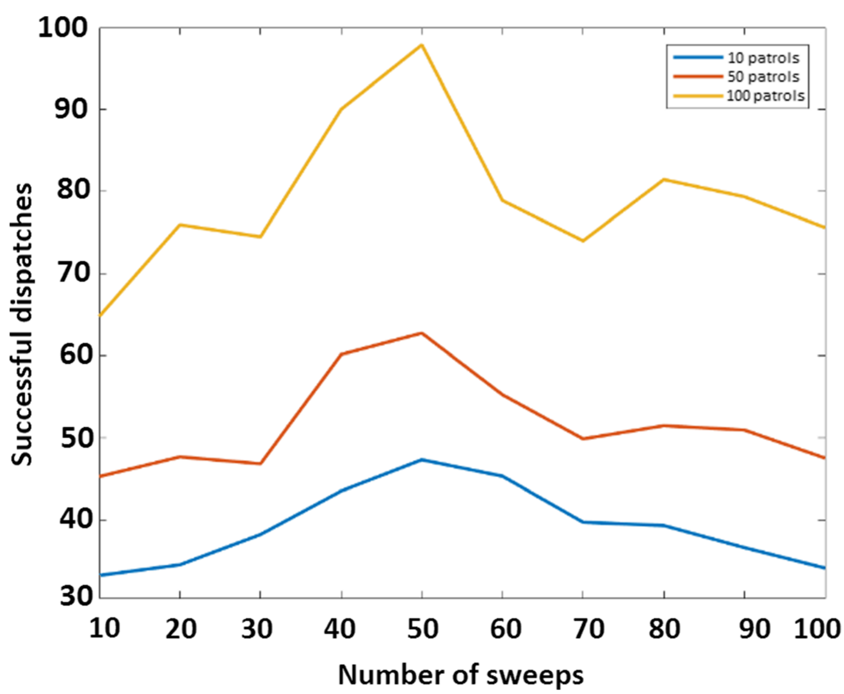

Fig. 6 Variation of successful reallocation ratio using the MRF-MDP scheme according to the number of sweeps for 10, 50, and 100 patrols

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