Integrated Motorway Traffic Control using Reinforcement Learning

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Integrated traffic control strategies are those that aim to combine different control measures into one system, resulting in a much more flexible and effective model that can be used in a wider variety of scenarios when compared to only using single measures or multiple uncoordinated systems. For example, one advantage of integrated strategies is that they can be used to coordinate intersections across urban and motorway networks [1]. This can be beneficial as conditions on one are usually influenced by the other, such as where queuing on motorway on-ramp spills back onto local roads [2]. Typically, these systems aim to combine measures such as Variable Speed Limits (VSL), Variable Message Signs (VMS), Route Guidance (RG) and ramp metering [3, 4, 5]. VSL manages congestion by dynamically adjusting the speed limit according to traffic conditions (usually between 60 and 120km/h) and is also important in increasing traffic safety by homogenising and reducing the speed of vehicles [6]. One simulated case study in Toronto showed that VSL was able to reduce the potential of a crash by 5-17% [7]. VSL is also effective at improving the performance of ramp metering measures, as combining the two can significantly improve total travel time when there is limited queuing capacity on a ramp [8]. Most VSL algorithms are either categorised as optimal control algorithms, such as model predictive control [9], or rule-based algorithms, such as fuzzy logic controllers [10]. However, deep-reinforcement learning (DRL) approaches have also been applied to VSL, including actor-critic networks [11]. RG, also called dynamic rerouting, can be useful in cases of non-recurrent congestion as it aims to route drivers away from unpredictable and congested conditions, such as those caused by accidents [12]. This is typically done by calculating a new optimal route once congestion or an incident has been detected [13] and is implemented through VMS located on gantries above the motorway. Similarly, VSL is implemented through some variation of VMS or digital information signs, although the amount of information given to drivers and their responses to the signs can vary [14].

Many integrated traffic control strategies use rule-based approaches where different control measures are selectively activated according to defined thresholds and the current conditions [15]. Framing traffic control systems as a non-linear optimisation problem also allows for the use of numerical optimisation [16] or evolutionary algorithms [17, 18]. However, there have also been many reinforcement learning (RL)-based strategies proposed, including many Q-learning applications, that combine ramp metering with VSL or VMS [19, 20]. In general, RL approaches have the advantage that they do not require prior knowledge of the environment to operate [21] and they avoid the sensitivity to traffic prediction methods in model predictive control [22]. For example, Q-learning learns to relate possible environment states to an optimal action to take, and is proven to always converge to an optimal solution [23]. Unfortunately, as this is done by updating a lookup table with discretised state and action sets, this type of algorithm can have limited applicability to problems with complex, continuous spaces when not using a function approximator [19]. The advantages of RL approaches also come with many other challenges in their design, particularly when focusing on coordinated systems, such as the issue of scalability. The "curse of dimensionality" is a well-known issue within reinforcement learning and refers to the dramatic increase in computational resources and training data needed as the state-action space grows [21]. In coordinated traffic management, this becomes apparent as the network and the number of control points become larger, and the algorithm has to consider more data, learn more parameters and generate more actions. To combat this, many decentralised learning approaches have been proposed [3, 19, 24] that aim to share the computational load and data across multiple individual agents that can learn and coordinate with each other.

This research will therefore aim to analyse how can we design an effective, and importantly scalable, framework for integrated traffic control systems that coordinates multiple control measures such as ramp metering, variable speed limits and message signs. This will be achieved through four studies, each analysing different aspects of RL and DRL-based systems. The first two studies will involve researching traffic state classification and examining how to consider both local and network-wide information during operation. They will also consider how to balance agents acting cooperatively and competitively where they may interfere with one another. The third study will focus on evaluating centralised and decentralised learning, and analyse how to most efficiently coordinate large numbers of agents. Lastly, the fourth study will focus on ramp metering and queuing considerations, specifically how to use network queue capacity and balance optimising mainline flow and reducing delays at on-ramps. Ultimately, the research will culminate in the development of a new model using the framework, which will be applied to a simulated example of the motorway ring road around Rotterdam, and its evaluation in comparison to other methods.

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