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Review Article

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Artificial Intelligence-Based Real-Time Traffic Management

Abbas Kadkhodayi[1]*, Mohammad Jabeli[2], Hassan Aghdam[3] and Shahin Mirbakhsh[4]

[1]*Assistant Professor, Department of Transportation Engineering, Islamic Azad University, Iran*

[2]*Research Assistant, Department of Transportation Engineering, Islamic Azad University, Iran*

[3]*PhD student, Department of Transportation and Civil Engineering, Azad University, Iran*

[4]*Research Assistant, Department of Road Transportation, Chamran Ahvaz University, Iran*

[*]Corresponding Author
Abbas Kadkhodayi, Assistant Professor, Department of Transportation Engineering, Islamic Azad University, Iran.

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Abstract
The paper proposes applying the ant colony optimization algorithm within a distributed multi-agent architecture, leveraging IoT technology, to address path routing challenges in urban traffic. The study emphasizes the potential of advanced AI techniques and multi-agent systems in revolutionizing traffic management for efficient and sustainable urban transportation systems. Our study addresses the challenging issue of traffic congestion in modern urban areas and the limitations of traditional solutions like road expansion and network indicators. To effectively tackle traffic congestion, the study explores various strategies that analyze traffic elements, falling into the Macroscopic and Microscopic Models. However, conventional traffic modeling faces significant challenges in dealing with complex traffic systems. The rise of the Internet of Things (IoT) offers opportunities for effective traffic analysis by collecting vast and uncertain data. Nevertheless, most existing systems focus on local events, leaving a gap in their effectiveness. To address this, multi-agent systems become a novel strategy, deploying distributed agents across road intersections for comprehensive traffic management. Artificial Intelligence (AI) techniques, including fuzzy logic, evolutionary algorithms, neural networks, and reinforcement learning, emerge as promising solutions for traffic control. For instance, artificial neural networks accurately predict urban traffic flow, and meta-heuristic AI approaches like the artificial bee colony algorithm optimize signal timings.

1. Introduction
Traffic congestion has become an increasingly challenging problem in modern urban areas, significantly impacting the quality of life over the past few decades. It poses major economic, societal, and environmental issues. Classical solutions, such as road network indicators and urban road expansion, have been proposed to address the problem, but the rapid growth of urban traffic has rendered these approaches inadequate [1,2]. Various strategies and innovations have been examined to effectively address traffic congestion, with a primary focus on analyzing the behavior of traffic elements like roads, signal controllers, and vehicles. These approaches can be broadly used to alleviate daily transportation network congestion, human health, considering new Active Traffic Management (ATM) policies that could present a promising and cost-effective solution for enhancing traffic network performance [3-5].

Generally, these strategies can be broadly categorized into two types:

1. The Macroscopic Model: This approach aims to provide a broad overview of traffic flow in a road network. It allows for the rapid extraction of short-term results but lacks the ability to perform detailed traffic analysis.
2. The Microscopic Model: In contrast, this model delves into the finer details of individual vehicle behavior and interactions within the road network. However, it struggles to precisely determine macroscopic traffic features, such as road capacity, vehicle queue lengths, and occupancy.

Conventional traffic modeling and control methods face significant challenges in dealing with systems with both symbolic and continuous dynamics, managing distributed asynchronous networked environments, achieving high-level coordination and autonomy, and constructing reliable systems from unreliable components [6]. The non-linear, fuzzy, and nondeterministic nature of traffic control systems further complicates the situation. Fortunately, the field of Artificial Intelligence (AI) has emerged as a promising solution to address these complexities

[7]. AI techniques, such as fuzzy logic, evolutionary algorithms (EA), neural networks, and reinforcement learning (RL), have shown remarkable potential in developing efficient traffic control systems [8]. For example, by combining artificial neural networks (ANN) with statistical approaches, one-hour forecasts of urban traffic flow rates have been achieved, with neural assembling models providing the most reliable and accurate estimations [9]. Moreover, connected automated vehicles (CAV)-based intersection control systems, which are based on costly physical traffic lights and based on a pixel reservation will no longer be a necessity in full multi-person vehicles (MPR) of autonomous vehicles (AVs) [10].

On the other side, meta-heuristic AI approaches, like the artificial bee colony (ABC) algorithm, have been successfully employed to optimize signal timings in coordinated road networks. Comparisons between different methods, including genetic and hill climbing methods, have demonstrated that the ABC method outperforms others in enhancing network performance [11]. Furthermore, the rise of the Internet of Things (IoT) has garnered attention as a solution to urban traffic problems. Its ability to collect vast amounts of complex and uncertain data daily offers new opportunities for effectively analyzing and addressing traffic issues [12,13]. These advanced approaches bring hope for creating more efficient and sustainable traffic management systems in the future.

However, alternative perspectives shed light on the traffic problem, considering its unpredictable nature, variable events, and the intricacies of the traffic environment. Regrettably, most existing systems only concentrate on local events, failing to grasp the overall traffic picture. Consequently, local agents remain limited to handling local events, leaving a gap in their efficacy [14]. To overcome this limitation, the adoption of multi-agent systems has emerged as a novel strategy, enabling a comprehensive and accurate approach to traffic management through the deployment of distributed agents across road intersections [15,16].

This paper aims to apply the ant colony optimization meta-heuristic algorithm within a distributed multi-agent architecture to address the path routing challenge in urban traffic, leveraging the capabilities of IoT technology. The organization of the paper is as follows: Section I provides an overview of the major optimization algorithms employed in ANNs by researchers to address this problem. Additionally, it introduces the essential concepts utilized in our model, namely, IoT technology and the multi-agent system in section II and introduces ACO.

1.1. Section 1

1.1.1. Artificial Neural Networks Approach

Artificial Neural Networks (ANNs) are highly potent data models that mimic the computational capabilities of the human brain. They have gained widespread application across various fields due to their ability to perform "intelligent" tasks similar to those of the human brain and their capacity to capture and represent complex input/output relationships. A neural network consists of multiple parallel processors, each with its own knowledge sphere and access to data in its local memory. Different types of networks have been developed, including single layer networks, multilayer networks, self-organizing networks, and recurrent networks, depending on their intended purpose and the problems they are designed to solve [17,18].

The versatility of ANNs makes them valuable in diverse domains such as classification, robotics, information and signal processing, predictions, and optimization techniques. Their effectiveness lies in their ability to address complex problems involving nonlinearity, self-organization, self-adaptation, and self-learning systems [19]. Consequently, researchers have extensively investigated the applicability of ANNs in traffic flow prediction.

Over the last few decades, numerous studies have demonstrated the feasibility of traffic flow prediction using ANNs. For instance, a study Muntean et al, focused on the stability and efficiency of short-term traffic volume prediction for non-urban highways under heterogeneous conditions [20]. The research utilized past traffic data, incorporating variables such as traffic volume, speed, density, time, and day of the week as input [21]. The results revealed that the ANN model consistently performed well and accurately predicted vehicle count, even when considering the speeds of different vehicle categories separately as input variables. Additionally, the model remained effective even when extending the time interval for prediction from 5 minutes to 15 minutes.

1.1.2. Reinforcement Learning

Reinforcement Learning (RL) represents a learning paradigm that encompasses both a learning problem and a specific area within machine learning. Unlike supervised learning, where the learning method relies on sample input-output pairs of the function to be learned, RL is distinctively characterized by an agent that interacts with its environment [22]. The agent takes actions and receives feedback in the form of reinforcement signals, but it is not explicitly informed of the correct actions to achieve its goals.

In this context, RL is applied to optimize the green timing in urban roads by processing traffic data collected through sensors to deduce information about vehicle behavior. The proposed approach utilizes an RL algorithm to enhance both the mean time delay and speed in the traffic flow. Each intersection in the road network is controlled by an individual agent, and these agents communicate with adjacent agents to exchange information (as depicted in Figure 1).

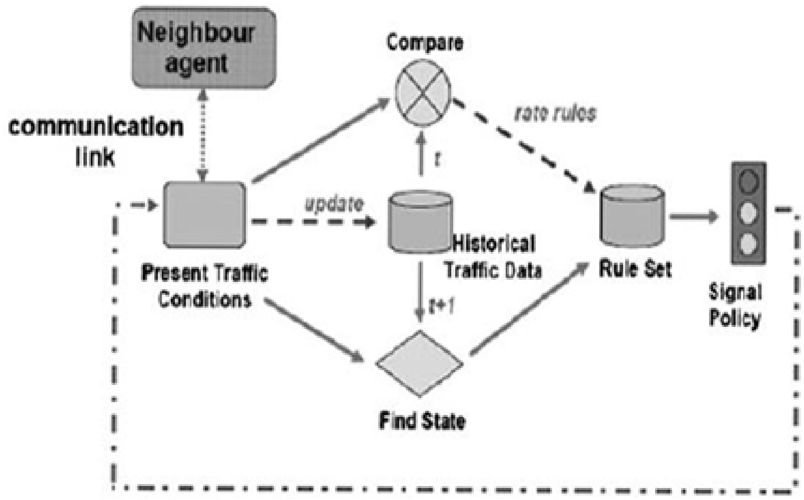

Figure 1: Agent-Based Architecture for Urban Traffic Signal Control

The agents within this multi-agent architecture learn a decision model for each intersection by observing the expected utility associated with state-action pairs and updating their knowledge using online Q-learning. To facilitate efficient information sharing and create a global view, an Online Q-learning approach has been adopted, and a Q-matrix is shared among the agents. This collaborative process enables agents to improve their local observations and collectively work towards optimizing the traffic signal timings for the entire road network.

1.1.3. Multi-Agent System

Multi-agent systems (MAS) have long been a captivating and highly regarded field of research, offering an effective solution for tackling diverse and intricate distributed problems due to their modular and adaptable structure. In MAS, multiple independent agents coexist in the same environment, capable of interaction and communication through message exchange, each pursuing its distinct goals and interests. This approach involves breaking down complex problems into more manageable sub-problems, which require less expertise compared to individual problem-solving. By employing a group of software agents collaborating harmoniously, the MAS approach seeks to achieve the global optimal solution, making it particularly applicable in various domains, including urban traffic management due to its geographically distributed nature.

In a study, two distinct traffic signal control agent architectures are introduced [1]. In the first model, the architecture comprises three layers: the lowest layer houses intersection controller agents (ICA) responsible for individual pre-assigned intersections, the middle layer consists of zone controller agents (ZCA) overseeing multiple pre-assigned ICAs, and the highest layer involves a regional controller agent (RCA) governing all the ZCAs. The second model explores three distributed agent models that employ different decision-making approaches for urban traffic control. In this model, each agent possesses a local perspective of its environment, making action decisions based on its perceptual capabilities.

Through simulations on a road network featuring twenty-five interconnected signal-controlled intersections and using the PARAMICS micro-simulator for the traffic network, the results reveal the distinct advantages and disadvantages of each architecture. However, overall, the multi-agent-based traffic signal controllers outperformed conventional controllers. These findings underscore the significant potential of multi-agent systems in enhancing signal control methods and their implementations on road networks, affirming the superiority of this approach in urban traffic management.

Lee et al developed a multi agent control system based on classic physics model know as spring-mass-damper model. This study revealed that multi agent approach suits well not only for advanced machine learning based models, but also in dealing with conventional and classic models [23].

1.2. Section 2

1.2.1. Urban Traffic Optimizer Model

The optimization algorithm model utilized in this study is the ant colony optimization (ACO) algorithm, which has proven effective in solving complex combinatorial optimization problems. Such problems involve numerous combinations of decisions and variables that need to be explored to identify near-optimal solutions. The ACO algorithm draws inspiration from the behavior of real ants, who communicate by using pheromones to find food. This communication method, known as stigmergy, offers significant advantages when a large number of individuals need to exchange extensive information. It can also be utilized in traffic management programs during challenging situations, such as controlling the movement of ambulances. There is a significant need to manage and optimize these models in emergency situations [24].

In this model, we specifically focus on the ant colony optimization meta-heuristic algorithm, wherein the ant colony is represented by a multi-agent system, and each artificial ant is represented by a single computational vehicle agent (VA). The transport network comprises various geographic locations interconnected by spatial routes. To represent the urban traffic network, we employ a graph-theoretic approach, effectively capturing the interconnectedness and relationships between different locations within the system. this way, we suggest a non-oriented graph G= {V, E}, where V= {v1, v2, v3, v4,…} is a finite set of nodes called intersections, and the pathways that link or connect between some pairs of nodes are called edges, roads, avenues, streets or lines which we represent by E = {e1, e2, e3,…} as shown in Figure 2.

$$p(c_i^j|Sp) = \frac{\tau_{ij}^{\alpha}.\,[\eta C_i^j]^{\beta}}{\Sigma_{c_i^j \in N(Sp)} \tau_{ij}^{\alpha}.\,[\eta(c_i^j)]^{\beta}}, \forall c_i^j \in N(Sp)$$

Figure 2: At the initialization step, all W_{ij} variables are initialized to a constant value τ0, after that, each VA presents a solution for the problem asynchronously and concurrently via the generate Solutions function by traveling on the graph through adjacent intersections and by building paths on G. Thus, at each iteration i of the algorithm, each VA applies a local decision C_{ij} of its current state proportional to the quality of the solution represented, and move to one of these according to a probabilistic intersection transition rule which takes the above-mentioned form.

Incrementally, VAs build solutions to the optimization problem by memorizing the best results in each iteration. Once the solution has been built, the weights are updated using the pheromone Update, and then will orient the next Vas [25].

Besides ant' activity, two more procedures are included by the ACO algorithm:
(1) the daemons actions which are used in our model, in order to centralize actions at the central agent (CA) who possesses the global knowledge, such as the activation of local optimization procedure, guiding vehicles to reach their destination by avoiding accidents and blocked roads.
(2) the so-called evaporation mechanism that decreases pheromone intensity level of all, in order to avoid the algorithm to converge too quickly to a sub-optimal region, and hence favors exploration of new regions of the search space.

1.2.2. Communication Architecture Model

In modern times, vehicles are equipped with multiple sensors and smart devices that provide them with real-time information about their current states, including position, speed, distance from adjacent vehicles, acceleration, and fuel consumption, among others. Utilizing this data, each computational vehicle agent (VA) remotely shares its current state with both the origin intersection controller agent (ICA-O) and destination intersection controller agent (ICA-D) within the road it is engaged in, as illustrated in Figure 3.

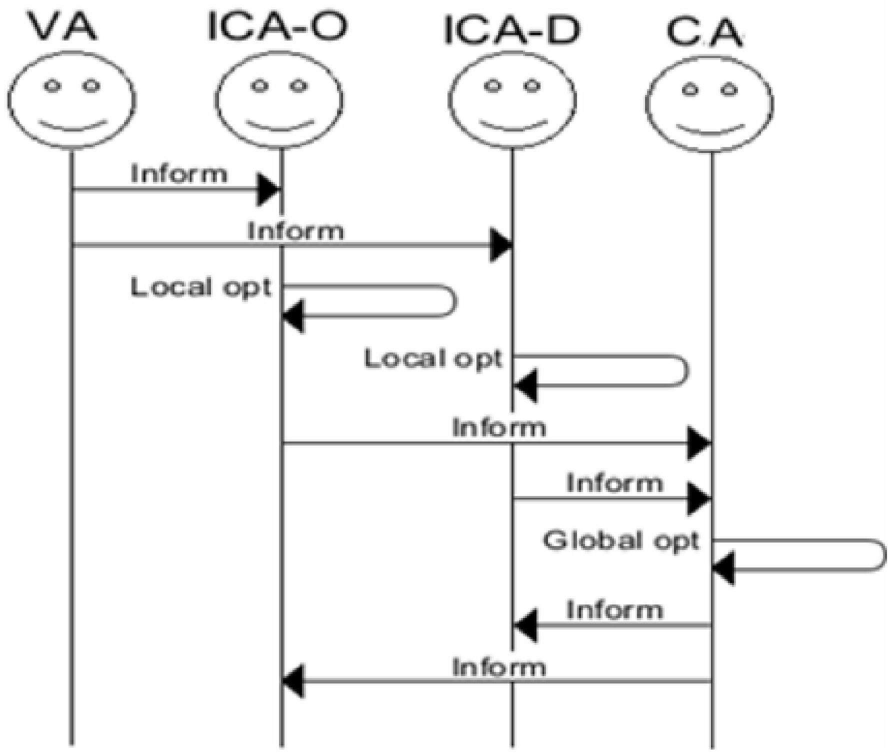

Figure 3: Sequence Diagram Representing the Process of Communication Within our Multi-Agent System

By exchanging this information with adjacent ICAs, they gain a local view of their assigned intersection, which includes metrics such as occupancy rate, traffic flow, density, fuel consumption, and accident reports, all in real-time [26,27]. Subsequently, the central controller agent (CA), responsible for supervising the affected limited space, collects information from all ICAs and can thus formulate an optimal global performance. This approach aims to enhance traffic operations, reduce accidents, and guide travelers to select the most efficient routes by utilizing relevant indicators derived from the comprehensive data shared among the intelligent agents in the system.

2. Conclusion

The study highlights the limitations of conventional traffic modeling and control methods, especially in dealing with the complexities of modern traffic systems. The non-linear, fuzzy, and nondeterministic nature of traffic control systems further complicates the situation, demanding innovative solutions. In this regard, the field of Artificial Intelligence (AI) has emerged as a promising avenue to address these challenges. AI techniques, such as fuzzy logic, evolutionary algorithms, neural networks, and reinforcement learning, have shown great potential in developing efficient traffic control systems.

Specifically, we have explored the application of artificial neural networks in traffic flow prediction, where their ability to capture and represent complex input-output relationships has demonstrated accurate and reliable results. Reinforcement learning, another AI approach, has been used to optimize the green timing in urban roads, showing promise in reducing mean time delay and improving traffic speed.

We also have addressed the critical issue of traffic congestion in modern urban areas, which has posed significant economic, societal, and environmental challenges over the past few decades. Traditional solutions, such as road network indicators and urban road expansion, have proven insufficient in handling the exponential growth of urban traffic. To tackle this complex problem effectively, we have explored various strategies that focus on analyzing the behavior of traffic elements, including roads, signal controllers, and vehicles.

The manuscript proposes a novel approach that combines the ant colony optimization (ACO) algorithm with a distributed multi-agent architecture to address the path routing challenge in urban traffic. Leveraging the capabilities of IoT technology, this approach promises to optimize traffic operations, reduce accidents, and guide travelers in selecting the most efficient routes.

Overall, this study showcases the potential of advanced AI techniques and multi-agent systems in revolutionizing traffic management, offering a promising path towards more efficient and sustainable urban transportation systems. The comprehensive exploration of various AI methods, their implementation, and their comparative performance provides valuable insights for researchers and practitioners seeking to address traffic congestion and enhance urban mobility in the modern era.

Moreover, the paper delves into the concept of multi-agent systems, which offer an effective approach to managing distributed and complex traffic problems. The study introduces different traffic signal control agent architectures, each with its own advantages and disadvantages, but collectively demonstrating the superiority of multi-agent-based traffic signal controllers over conventional methods [28-34].

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