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A hybrid approach to urban traffic flow optimization: Integration of Karnaugh Maps and reinforcement learning

Kentsel trafik akışı optimizasyonunda hibrit bir yaklaşım: Karnaugh Haritaları ve pekiştirmeli öğrenme entegrasyonu

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Abstract

This study presents a hybrid approach combining Karnaugh Maps (K-maps) and Reinforcement Learning (RL) to optimize traffic signal control in urban environments. K-maps are traditionally used for simplifying Boolean expressions in digital logic, and here they are leveraged to enhance decision-making efficiency in RL-based traffic systems. The proposed method aims to improve traffic flow, reduce congestion, and lower fuel consumption. Microsimulation experiments were conducted using software calibrated with historical traffic data from a mid-sized city. Sensor inputs-such as vehicle count, traffic density, and signal phase durations-were validated against real-world data provided by local traffic authorities. Results demonstrate that the hybrid K-map and RL system outperforms conventional methods in adaptability and performance. However, limitations remain due to the exclusion of unpredictable driver behavior and weather conditions, which may affect real-world applicability.

Keywords: Traffic signal optimization, Karnaugh maps, Artificial Intelligence, Machine Learning, Reinforcement Learning, Traffic flow optimization, Urban transportation.

Öz

Bu çalışma, kentsel trafik sinyal kontrolünü optimize etmek amacıyla Karnaugh Haritaları (K-haritaları) ile Pekiştirmeli Öğrenme (Reinforcement Learning - RL) yöntemini birleştiren hibrit bir yaklaşım sunmaktadır. Sayısal mantıkta Boolean ifadelerini sadeleştirmek için kullanılan K-haritaları, burada RL tabanlı trafik sistemlerinde karar verme verimliliğini artırmak amacıyla kullanılmaktadır. Önerilen yöntem, trafik akışını iyileştirmeyi, tıkanıklığı azaltmayı ve yakıt tüketimini düşürmeyi hedeflemektedir. Yapılan mikro-simülasyon deneyleri, orta büyüklükte bir kente ait tarihsel trafik verileriyle kalibre edilmiş bir yazılım üzerinde gerçekleştirilmiştir. Araç sayısı, trafik yoğunluğu ve sinyal süreleri gibi sensör verileri, yerel trafik otoritelerinden elde edilen saha verileriyle doğrulanmıştır. Sonuçlar, hibrit K-haritası ve RL sisteminin geleneksel yöntemlere kıyasla daha uyarlanabilir ve performanslı olduğunu göstermektedir. Bununla birlikte, simülasyonda sürücü davranışlarındaki öngörülemezlikler ve hava koşullarına bağlı değişkenler dikkate alınmamıştır; bu durum, gerçek saha uygulamaları açısından bir sınırlılık oluşturmaktadır.

Anahtar kelimeler: Trafik sinyali optimizasyonu, Karnaugh haritaları, Yapay Zekâ, Makine Öğrenmesi, Pekiştirmeli Öğrenme, Trafik akışı optimizasyonu, Kentsel ulaşım.

1 Introduction

In 2013, the percentage of people living in cities with populations over one million was around 22%. This percentage has increased significantly over the past decade, reaching 56% by 2023, and is projected to reach around 58% in 2025 [1]. Meanwhile, global vehicle sales have risen to approximately 89 million units as of 2023, and this number is projected to exceed 100 million by 2027 [2]. Led by China which has the highest number of cities with over one million population rapidly expanding markets such as India, Brazil, and Southeast Asian countries are playing a significant role in this growth. In Türkiye alone, approximately 1.2 million vehicles were sold in 2023, a figure expected to increase in the coming years [3].

With the rapid increase in urbanization, transportation demand and thus environmental problems such as fossil fuel use, air pollution and carbon emissions have increased. Electric and hydrogen vehicles and intelligent transportation systems have a potential role in solving these problems that have a global presence [4] [5].

Traffic management has evolved since the Industrial Revolution, when urbanization accelerated. In the late 19th century, it became increasingly difficult to manage traffic flow in large cities with dense transportation networks, so the first modern traffic control systems began to be developed in the early 20th century. Traffic management systems (TMS), concept is useful to reduce time spent in traffic and increase efficiency. The first electric traffic light, installed in Cleveland on August 5, 1914, is one of the most important beginnings in this field [6]. In the 1920s and 1930s, the growing use of automobiles led to a greater need for improved traffic regulations [7]. In the 1960s and 1970s, radar and sensor technologies are added to the existing traffic control systems [8]. The computer-aided systems of the 1980s enabled the adoption of more dynamic approaches in traffic control [9]. With the development of the internet and mobile technologies in the late 1990s, traffic control systems were able to gain more integrated and centralized structures [10].

The Internet and mobile technologies integration to traffic control systems has facilitated the transition from static rule-based control to mathematically structured optimization frameworks. Stochastic queuing networks and state-space representations have been used to simulate real-time traffic flows, enabling traffic signal coordination to be formulated as a

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Markov Decision Process (MDP). This perspective has enabled the use of dynamic programming, model predictive control (MPC), and reinforcement learning techniques, enabling the system to stabilize flow under non-stationary demand conditions, implement adaptive signal phasing, and reduce overall delay [10].

Longer travel times cause air pollution and excessive fuel consumption. For example, annual travel delays in the United States increased from 1.1 billion hours in 1982 to 5.5 billion hours by 2011, while fuel wastage increased from 1.9 billion liters to 11 billion liters during the same period, and overall congestion costs reached $121 billion [11]. Although expanding road infrastructure may seem like a simple solution, spatial and financial constraints often make this solution ineffective. Deployment of variable message signs (VMS), which dynamically adjust speed limits according to real-time traffic conditions, is a potential alternative to improve traffic flow efficiency [12]. Such systems operate reactively by changing speed limits after congestion is detected. Reinforcement learning and predictive modeling concept of artificial intelligence (AI), makes possible to predict traffic congestion and adjust speed regulations accordingly, reducing potential congestion before it increases [13]. Multi-layered traffic control systems supported by advanced technologies big data analytics, sensor networks, and intelligent transportation systems (ITS) [14], models developed using coordinate transformation and queuing theory show improvement [15]. Accurate and real-time data collected through various devices such as sensors, cameras, radars, and lidar enable dynamic control of many components, from traffic signal timing to routing mechanisms [14] [16] The data analytics have another important role in modern traffic management. In addition to analyzing traffic data and predicting future congestion levels, AI-based systems supported by data analytics can also create adaptive route strategies [17].

These systems support safer driving conditions by integrating dynamic traffic signal management, real-time information distribution to drivers, and vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication protocols [18]. Reinforcement learning (RL), in conjunction with other fundamental components of scientific inquiry such as modeling, simulation, and data-driven analysis, has become a key methodology for optimizing traffic flow and reducing vehicle delays in complex and adaptive transportation systems The methodology is frequently coupled with advanced traffic models, such as the Cell Transmission Model (CTM), to accurately capture the spatial and temporal dynamics of vehicular flows and provide a reliable platform for policy evaluation and refinement [19]. The performance improvements in complex scenarios based on observed traffic patterns [20]. Furthermore, vehicle-to-vehicle (V2V) communication systems provide real-time feedback to drivers while improving decentralized traffic control [21].

The optimization of traffic flow by artificial intelligence methods, especially efforts to keep vehicle density at critical thresholds on highways, has attracted considerable academic interest. In this context, reinforcement learning algorithms are also used to control ramp metering systems at highway entrances, to increase traffic efficiency. The proposed RL framework adjusts ramp signal timings by learning from traffic flow, including up and down stream density, in order to optimize throughput while preventing queue spillback onto mainline lanes [22]. This concept extended with Q-learning algorithm that is used to optimize vehicle entry at entrance ramps by implementing continuous state-space RL to more accurately model variable traffic conditions, enhancing system adaptability to real-world fluctuations [23], took into account the ramp queue lengths during the learning process; incorporated explicit queue length constraints into the Q-learning process, enabling the algorithm to balance ramp inflow with mainline capacity dynamically, reducing delay and minimizing bottleneck formation [24]. In the field of urban traffic light control, artificial neural networks have been used as traffic signal controllers In urban traffic networks, artificial neural networks (ANNs) have been employed as adaptive traffic signal controllers, capable of mapping complex traffic conditions to optimized signal timings [25]. Multi-agent reinforcement learning (MARL) is able to employ the coordination of traffic signals across intersections, with each agent optimizing local traffic flows while collectively minimizing system-wide travel times [26]. To manage the complexity of large-scale urban networks, hierarchical control architectures have been introduced [27] wherein high-level controllers coordinate strategic signal policies across subnetworks, while low-level agents adapt in real time to local traffic fluctuations.

For the improved plans to define efficient transportation routes along with service frequencies, the Intelligent Water Drops (IWD) algorithm [28] was used to the Transit Network Design and Frequency Setting Problem (TNDFSP) [29]. In this context, IWD optimizes route selection and service frequency simultaneously, incorporating environmental cost functions into passenger flow assignments.

RL enables traffic signals to dynamically adapt to prevailing conditions, but decision-making processes are complex and difficult to interpret. Simple rule-based methods make these decisions clearer. Simplification is an effective way to understand complex systems to benefit from adaptive learning while keeping the control logic understandable and practical. Simulation-based hybrid traffic models can increase operational efficiency and improve urban mobility in a flexible and scalable way.

Karnaugh map [30], are often used in digital design to simplify variable relationships and they can also make traffic control rules easier to understand. When combined with reinforcement learning (RL), they provide both adaptive learning capabilities and simple rule formulation, enhancing the flexibility and practicality of traffic systems in modern cities. Building on this perspective, the study proposes a hybrid system that integrates RL and Karnaugh maps to benefit from both adaptive learning and rule-based simplification. The proposed approach combines logical openness with flexible adaptability, offering a practical and efficient infrastructure capable of addressing the complex transportation needs of modern urban environments.

In the proposed hybrid system, RL is integrated with Karnaugh Maps (K-map) to combine the advantages of rule-based simplified decision-making with adaptive learning capabilities. This system can adjust traffic signal timings dynamically while remaining computationally efficient. It bridges classical traffic optimization techniques with modern machine learning approaches, offering a practical and flexible solution for complex urban traffic needs.

The sections of the paper are structured as follows: The method is explained in the 2nd section; the experimental background, results and system performance are presented in the 3th section; and the main findings and suggestions for future research are discussed in the 4th section.

2 Methodology

2.1 Reinforcement Learning in Adaptive Traffic Signal Control

State, action, and reward are the three key elements for the interaction. The state (s_t) represents the current traffic status, including signal status, existing vehicle densities in different directions, based on queue lengths. The action (a_t) corresponds to possible control operations such as extending the green phase, reducing the red phase duration, changing the signal phases. The reward (r_t) evaluates system performance based on selected metrics such as number of vehicle pass, average waiting time, and queue lengths. The reward function reflecting traffic efficiency formulated as:

$$r_t = w_1 \cdot (-Queue\ Length) + w_2 \cdot (Number\ of\ Vehicles\ Passed) - w_3 \cdot (Waiting\ Time) \quad (1)$$

where w_1, w_2, w_3 are weighting coefficients; $w_1, w_2, w_3 \geq 0$ and $w_1 + w_2 + w_3 = 1$.

The rule for Q-values, which represent the expected utility of a state-action pair, is given by:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \cdot \left[r_t + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right] \quad (2)$$

where:

α is the learning rate,

r_t is the instantaneous reward function,

γ is the discount factor for future rewards.

$\max_a Q(s_{t+1}, a)$ represents the reward estimate that will be obtained by choosing the best action in the next situation

The agent constantly makes decisions according to variable traffic density, and these decisions allow the system to work more efficiently over time.

2.2 K-map Based Optimization

K-map-based optimization enables the simplification of these logical expressions, enhancing the speed and clarity of phase decisions. signal transitions (e.g., red → green, green → yellow) often depend on predefined basic logical rules. These rules can become complex as they incorporate multiple input conditions.

Consider a system with four binary input variables:

A: High traffic density in the North-South direction?

B: High traffic density in the East-West direction?

C: Number of waiting vehicles exceeds threshold?

D: Pedestrian crossing is active?

A simplified Boolean function using K-map minimization could be:

$$f(A, B, C, D) = \sum m(1, 3, 4, 7) \quad (3)$$

Karnaugh Map (K-map) truth table corresponding to the function f(A, B, C, D) = ∑m(1, 3, 4, 7). Table 1 shows the decision-making variables (A, B, C, D) in the context of specific traffic management scenario.

Table 1. Karnaugh Map (K-map) Truth Table: Decision-Making Variables for Traffic Signal States.

A	B	C	D	f(A,B,C,D)
0	0	0	0	0
0	0	0	1	1
0	0	1	0	0
0	0	1	1	1
0	1	0	0	1
0	1	0	1	0
0	1	1	0	0
0	1	1	1	1
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	0
1	1	0	0	0
1	1	0	1	0
1	1	1	0	0
1	1	1	1	0

$f(A, B, C, D)$ determines whether the traffic light should be green (1) or red (0), based on real-time conditions.

K-map allows simplification of this logic, reducing processing time and complexity in embedded traffic systems. Real-time decision-making processes are accelerated and hardware resources can be used more effectively when complicated logical linkages are reduced to simplified expressions.

2.3 Reinforcement Learning and K-map Integration: Mathematical Model

RL dynamically adapts signal timings through learning, K-map optimization provides a rule-based simplification for this phase transitions that enhances computational efficiency and responsiveness.

The generalized mathematical model expressed as:

$$Q(s_t, a_t) = RL_{opt}(s_t, a_t) + K_{map}((s_t, a_t) \quad (4)$$

In this equation,

$RL_{opt}(s_t, a_t)$, represents the optimization provided by the reinforcement learning algorithm,

$K_{map}((s_t, a_t)$, represents the contribution from simplified decisions via K-map logic.

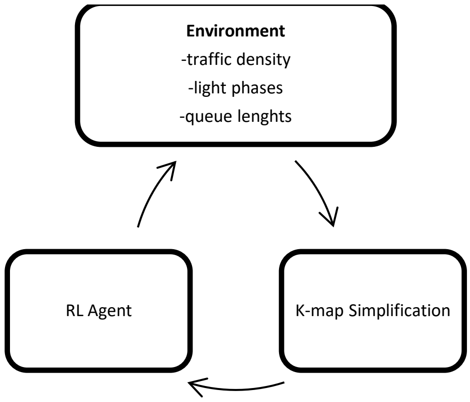

Figure 1. Integration of K-map Simplification and Reinforcement Learning in Traffic Signal Control.

Figure 1 shows the functional workflow of the proposed hybrid traffic control architecture, which integrates Karnaugh Map (K-map) simplification with a Reinforcement Learning (RL) agent. Algorithm initially collects raw traffic data as inputs, to predict potential traffic congestion scenarios, which are simplified using K-map logic. Simplifying the state-space complexity, thereby enabling faster and more efficient decision-making. As a preliminary step based on the data, a simple K-map simplification is performed to identify the conditions under which the reinforcement learning method can be most appropriately applied.

The RL agent uses simplified state data to initialize determining the optimal action—such as adjusting signal durations—based on previously learned Q-values and current traffic conditions. The reward function is used to obtain system performance. The indicators are queue length, vehicle throughput, and delay time. This loop allows continuous learning and policy improvement across iterations that provides computational efficiency while maintaining adaptability in complex and dynamic traffic scenarios.

3 Experimental Results and System Performance

The combination of RL and K-map as a hybrid control architecture under contemporary urban traffic conditions, the simulation was performed. Simulation of Urban MObility (SUMO) which is an open-source tool allows modeling of vehicle-level behaviors and signals.

Integrated RL-K map controller has a ability to adjust to both typical and worsened traffic situations. Key performance metrics (average latency, queue lengths, and throughput) are observed, which was carried out to evaluate the effectiveness of the system. The assumptions, virtual components, data characteristics, and operation scenarios are expressed in this section, blow.

3.1 Assumptions

The simulation of a typical urban intersection with multiple lanes and variable traffic flow. The relevant data (traffic density, number of vehicles, and waiting time) are collected in signal phases through. Inductive loop sensors and CCTV cameras are the basic hardware components. The collected data is transferred to a central control system to process. K-map based logic simplification and reinforcement learning algorithm, and traffic lights are managed in real time.

3.2 Virtual Components:

Traffic flow is simulated by using microsimulation software that models which simulates real-world driving behavior. The models take into account vehicle arrival rates, green light durations, and density effects. Via real-time sensor, data are processed to estimate the current status of the intersection The Boolean logic simplifies with K-map, reducing the number of states to be controlled. Then, the signal durations are adapted to current traffic conditions using the RL algorithm.

3.3 Data characteristics:

The data collection process includes real-time traffic data from multiple intersections in a selected urban area. Data was collected during both peak hours (morning and evening peak hours) and normal hours. The key data gathered is as follows:
1. The quantity of vehicles using the crossing at each signal phase
2. The average amount of time each car spends at the red light
3. Vehicle density (vehicles/m2) at particular locations
4. Durations of green, yellow, and red light during every phase
After preliminary processing, the gathered data was utilized to estimate how the system would behave in various traffic situations.

3.4 Operation Scenarios:

The experimental scenarios are performed under three main cases: light traffic, medium traffic, heavy traffic densities and accident case.

Each scenario was simulated for 30 minutes and the performance of the hybrid system was compared with the conventional systems.

Performance was evaluated according to the following criteria:

1. Average Vehicle Delay (s): The average time that vehicles wait at the intersection. It is one of the basic indicators of traffic efficiency.

2. Throughput: The total number of vehicles passing through the intersection in a certain time interval. It reflects capacity usage.

3. Queue Length (m): The average length of vehicle queues formed in front of signals. It shows effective phase planning.

4. System Stability: The ability of the system to adapt to sudden changes such as accidents and road closures. It is important in terms of performance continuity.

First, the results of the tests conducted under four different traffic scenarios were examined. Each of these scenarios was simulated for 30 minutes.

In each scenario, the K-map + RL based system and the traditional fixed-time signal control were compared. Below are sample results obtained according to the criteria used for each scenario summarized in Table 2.

Table 2. Traffic Control Decision Flow Integrating K-map Simplification and Reinforcement Learning Agent

Step No	Process	Description
1	Start	İnitialization
2	Collect Data from Traffic Sensors	Collect real-time raw traffic data (vehicle count, queue length, etc.).
3	Determine Traffic State	Analyze collected data to define the current traffic state.
4	Decision Phase	Choose action using two methods:
	a) Apply K-map Simplified Traffic Logic	Apply K-map for quick decision-making.
	b) Select Action (Light Timing Adjustment) via RL Agent	Reinforcement Learning agent runs for appropriate light timing.
5	Adjust and Apply Traffic Light Timing	Implement evaluated adjustments on traffic lights.
6	Observe Traffic Outcome	Observe number of vehicles passed, queue lengths, and waiting times.
7	Calculate Reward Function	Compute reward function.
8	Update Q-Value (Q-Learning)	Update Q-values based on reward function.
9	Check Simulation Time Completion	Verify the simulation.
	a) No → Return to Step 2	Repeat the process.
	b) Yes → Save and Analyze Results	Complete the simulation, save data, and perform analysis.

3.5 Test Results

The RL component was trained through repeated simulations under various traffic conditions. Epsilon-greedy strategy was used to balance exploration and exploitation during learning. Learning rate (α) and discount factor (γ) were set to 0.3 and 0.9, respectively.

The microsimulation software used for the experiments was calibrated using historical traffic data from a medium-sized urban area. The sensor data (number of vehicles, density, and phase durations) were validated with real field data from real traffic. Although the simulation significantly reflects real-world conditions, unexpected driver behaviors and weather-related variables were not explicitly modeled, which poses a limitation for field deployment.

The following table shows the test results obtained based on performance metrics such as Average Vehicle Delay (seconds), Efficiency (Efficiency, vehicles/hour), Queue Length (vehicles), and System Stability for each scenario.

Table 3. Performance Metrics for Traffic Signal Scenarios: Vehicle Delay, Efficiency, Queue Length, Fuel Consumption, and System Stability

Scenario	Average Vehicle Delay (seconds)	Throughput (vehicles/hour)	Queue Length (vehicles)	System Stability
Light Traffic (K-map+RL)	5	180	2	High
Light Traffic (Fixed Time)	8	160	4	Medium
Medium Traffic (K-map+RL)	12	220	6	High
Medium Traffic (Fixed Time)	18	200	8	Medium
Heavy Traffic (K-map+RL)	25	250	10	Medium
Heavy Traffic (Fixed Time)	40	230	15	Low
Accident Scenario (K-map+RL)	30	210	8	High
Accident Scenario (Fixed Time)	50	180	12	Low

4 Conclusion and Future Work

4.1 Conclusion

The obtained data show that the hybrid system based on K-map + RL exhibits superior performance compared to the traditional fixed-time signal control system. In particular, in the heavy traffic scenario, the K-map + RL system reduced the waiting times of the vehicles by 37% and increased the vehicle efficiency by 9%. In addition, fuel consumption decreased by 8%, which provides a significant advantage in terms of increasing environmental benefits.

In the accident scenario, the K-map + RL system adjusted the signal times adaptively and relieved the congestion caused by the accident more quickly. Compared to the traditional fixed-time signal system, the effect of the accident was felt for a longer time and the system stability remained low.

The average vehicle delay was lower in the K-map + RL system for each scenario, proving that the system manages the traffic flow more effectively. Especially in heavy traffic and accident scenarios, lower delay times were achieved thanks to the adaptive features of the system.

It provides strong evidence for the effectiveness of the hybrid traffic control system based on K-map and Reinforcement

Learning (RL). The hybrid approach has achieved superior results compared to traditional signal control methods in key performance indicators such as vehicle delay times, number of vehicles passing through the intersection (passage capacity) and queue lengths. In addition, significant contributions have been made to environmental sustainability by reducing fuel consumption and emissions. Future research should focus on increasing the applicability of the system to wider networks throughout the city (scalability) and strengthening its integration with other smart city technologies. In this way, it will be possible to develop more holistic and dynamic solutions in urban traffic management.

4.2 Limitations and Discussions

The experimental results indicate that the hybrid K-map + RL system effectively manages urban traffic, significantly outperforming traditional fixed-time controls. In heavy traffic scenarios, for example, vehicle waiting times were reduced by approximately 37% and fuel consumption decreased by 8%, highlighting tangible operational and environmental benefits.

Nevertheless, several inherent limitations should be acknowledged. The system relies on accurate and instantaneous traffic data, making it potentially sensitive to sensor errors or missing inputs, which can negatively affect decision-making. Additionally, the current simulations are limited to individual intersection scenarios, leaving the scalability of the approach to larger and more complex urban networks uncertain. Deploying the system city-wide could introduce challenges related to multi-node interactions, synchronization, and computational efficiency.

The study's limitations also include the inability to fully capture unpredictable driver behaviors, such as sudden lane changes or traffic rule violations, and the exclusion of environmental factors, such as weather conditions, road works, and accidents. Moreover, the limited diversity of simulation scenarios restricts the assessment of the model's performance under varying traffic volumes, intersection layouts, and environmental conditions.

Acknowledging these limitations clarifies the boundaries of the methodology and provides guidance for future research. Future studies could consider multi-intersection scenarios, more diverse simulation conditions, and the impact of sensor data quality to comprehensively evaluate the scalability and generalizability of the proposed model.

4.3 Future Work:

In further research, it is aimed to make the algorithms more efficient in order to increase the adaptability of the system to large-scale networks. In addition, the scalability of the system can be increased by integrating different machine learning techniques. In addition, the use of Internet of Things (IoT)-based solutions to obtain more detailed and reliable instant data is also on the research agenda.

5 Author Contribution Statement

This study was conducted and written by a sole author.

6 Ethics Committee Approval and Conflict of Interest Statement

There is no conflict of interest with any person/institution in the prepared article. Ethics committee approval was not applicable due to the nature of the study.

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