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Research Article

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A Review of Adaptive Signal Control Systems Based on Changes in Traffic Environments

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Abstract An overview of the increasingly important methods and applications of Adaptive Dynamic Programming (ADP) is presented. The current status and trends of research on key issues such as convergence, stability, and coordination in ADP are analyzed in detail. The characteristics of urban traffic signal control problems and the currently used control methods are introduced. Furthermore, the application status and prospects of ADP methods in the optimal control of traffic signals at urban intersections and freeway on-ramps are discussed.

Keywords Traffic signal control, ADP, EPGA, Bird Swarm Algorithm, GA.

1. Introduction

The adaptive traffic signal control system is an effective measure to alleviate urban traffic congestion. This system can dynamically adjust signal timing parameters in response to seasonal changes and short-term fluctuations in traffic demand, thereby enhancing the operational efficiency of urban road networks. With the advancing of informatics such as computer science, autonomous driving, vehicle-to-vehicle communication, and mobile internet, the means of acquiring traffic data have become increasingly abundant. Significant improvements in data collection include the increase in holographic data volume, the diversification of available data types, and the improvement in accuracy.

This paper delves into the development, technical characteristics, and current research status of commonly used adaptive signal control systems. Additionally, it examines signal control methods tailored for heterogeneous traffic flow composed of connected and autonomous vehicles. The conclusion drawn is that signal control based on multi-agent reinforcement learning represents a closed-loop feedback adaptive control approach. This method excels in real-time performance, accuracy, and self-learning capabilities compared to many similar methods. With its "model-free" and "self-learning" characteristics, it can effectively adapt to the abundance of traffic information data. Consequently, this method is considered a promising research direction for future traffic control methodologies.

Furthermore, the signal control system based on multi-agent reinforcement learning not only holds vast potential for widespread applications but also provides an entry point and technical support for the development of industries such as vehicle-to-X systems, connected vehicles, and autonomous driving. Therefore, the achievements related to adaptive control systems for future transportation environments exhibit extremely broad application prospects.

2. FPGA-Based Adaptive Traffic Signal System

As the number of road vehicles gradually increases, traditional fixed-timing traffic signal systems can no longer adapt to complex changes in traffic flow patterns. To address this challenge, an adaptive traffic control system based on FPGA technology is proposed, integrating inductive control methods with timed configuration schemes. The control programs for various modules are written in Verilog and compiled and simulated using Quartus II software. This system collects traffic flow information at intersections, provides real-time feedback, and automatically adjusts timing plans.

Road intersections vary in configuration, including T-junctions, three-way intersections, four-way intersections, and five-way intersections, among others [1]. Among these, four-way intersections are the most common. Min's research [2] focuses on a four-way intersection, designing a sensor circuit for traffic flow detection that records vehicle count data over a specified time interval. This data is stored in real-time and fed back to the main chip for processing, determining the timing plan for the next signal cycle [3,4].

Phase transitions at a four-way intersection are designed based on four phases with eight states, following the sequence of straight green light → yellow light → left-turn green light → yellow light → red light. When the red light is constantly lit in one direction, the other direction has a constantly lit green light. Each phase is assigned a value and a countdown timer, with the phase signal and countdown synchronized.

Table 1: Specific Timing Schemes for Each Phase Under Different Traffic Flow Data

	Vehicle Traffic Volume, n/pcu							
	n≤10	**[11,15]**	**[16,20]**	**[21,25]**	**[26,30]**	**[31,35]**	**[36,40]**	**n≥41**
Phase 1	5	20	25	30	35	40	45	50
Phase 2	5	15	20	20	20	25	25	30
Phase 3	5	20	20	25	25	30	30	35
Phase 4	5	15	20	20	20	20	25	25
Total Yellow	20	20	20	20	20	20	20	20
Time delay	80	90	105	115	120	135	145	160

Based on the fundamental principles of traffic signal design and the observation that traffic flow at intersections does not suddenly change within short periods, specific timing plans for each phase under different traffic flow conditions are derived from actual statistical data and empirical estimates collected at a particular intersection. These timing plans are presented in Table 1.

In Table 1 of the academic paper, the detected traffic flow data are divided into 8 intervals. In these intervals, when the traffic flow is less than 10, the shortest cycle timing scheme is adopted for the phase; when the traffic flow is greater than 41, the system adopts the longest cycle timing scheme. For traffic flow values between 10 and 41, each group corresponds to a unique timing strategy. Specifically, the first phase represents the duration of green light for through traffic in the main road direction; the second phase represents the duration of green light for left turns in the main road direction; the third phase represents the duration of green light for through traffic in the minor road direction; and the fourth phase represents the duration of green light for left turns in the minor road direction. During the transitions between the 4 phases, there is a 5-second yellow light transition period. The specific timing for each phase, along with the total yellow light delay time, constitutes the duration of one cycle.

The design of the adaptive traffic signal system is centered around the Hurricane 2nd generation FPGA development board, with the main chip model EP2C5T144C8N. This design incorporates various circuit modules including the power supply module circuit, reset module circuit, clock module circuit, and download configuration circuit. Additionally, it involves designing the traffic flow detection circuit and external analog display circuit, followed by physical soldering. Hardware connections are established by utilizing pin constraints to interface with the general I/O ports on the development board, forming a complete traffic signal system.

Furthermore, the system is programmed using Verilog hardware description language in a modular fashion. The modules designed in this research mainly consist of a clock division module, traffic flow detection and statistics module, signal conversion module, phase assignment module, countdown module, decoding display module, and adaptive decision-making module. Since the clock signal used is 1 Hz, and the system's built-in clock signal operates at 50 MHz, the clock signal is initially divided to serve as the timing signal for each phase and countdown.

Subsequently, vehicle flow data is collected and statistically analyzed using traffic detection sensors, providing real-time feedback to the main chip of the development board. Adaptive decisions regarding timing schemes are made based on this data through table lookup, and phase assignment outputs are generated. A countdown is displayed on the digital display, and the signal lights synchronize to transition phases accordingly, enabling real-time adaptive control of the signal system.

Comparatively, this design presents significant improvements over traditional traffic signal control systems. It effectively aids in directing traffic flow at intersections, alleviating traffic congestion to a certain extent. Hence, it holds considerable reference value and practical significance for improving domestic traffic signal systems.

3. Traffic Signal Control Based on Swarm Intelligence Algorithms

The Bird Swarm Algorithm is a model optimization algorithm, primarily based on the idea of utilizing a random search strategy with the fitness value as a criterion to explore the optimal control parameters in the parameter space. Therefore, this method is suitable for optimizing traffic signal control problems. Cao [6] investigated the application of the Bird Swarm Algorithm in traffic signal control systems and further enhanced the existing algorithm. Initially, through the study of Analytic Hierarchy Process (AHP) and the relevant theory of the Bird Swarm Algorithm, a focused examination of the fundamental principles, mathematical models, and parameter analysis of the Bird Swarm Algorithm was conducted. This led to the proposal of an improved method for parameter optimization in traffic control systems. Simultaneously, an analysis of the application of the Bird Swarm Algorithm was performed, deepening the understanding of the algorithm through a comparative study with existing relevant theories.

Subsequently, building upon the foundational theory of the Bird Swarm Algorithm, modifications were made to the basic algorithm with the aim of avoiding premature convergence issues and enhancing its performance significantly over the basic version. Finally, employing traffic simulation software, the road network model was constructed, and traffic simulation parameters were configured. The optimized and improved Bird Swarm Algorithm was then applied in simulation experiments for traffic signal control, aiming to validate its effectiveness in controlling aspects under the influence of multiple target expectations.

3.1 Control methods and approaches

When controlling traffic signals, the academic approach adheres to the following three main principles: (1) Each intersection serves as the core of traffic control, with global sub-optimization as the control objective, avoiding optimal control over the entire area or process; (2) Intelligent multi-objective control is applied to the travel process rather than solely controlling travel destinations; (3) Various aspects of real-world traffic travel demands are fully considered and reflected upon.

Based on these principles, this paper proposes an algorithmic optimization strategy consisting of two main components: an optimization algorithm and a simulation program. The optimization part is enhanced by the bird swarm algorithm to optimize the cycle period of traffic signal lights. The simulation program assigns a quantified value weight to solutions to optimize a given city's road network intersections. The entire simulation process is completed by simulating the traffic light cycle program to obtain simulation data, optimizing a new solution using the bird swarm algorithm, and updating the iterative simulation program. Subsequently, simulation of new instances begins, requiring the definition of elements such as streets, driving directions, obstacles, traffic lights, vehicle speeds, and routes during the traffic signal cycle process. Upon simulation completion, necessary global information is returned.

The evaluation result of each solution is a deterministic value because the solution is deterministically generated in the vehicle path simulation program. This evaluation value, termed the fitness value, serves as the criterion for optimization and fosters collaboration and competition among particles. In fact, random traffic simulation can yield similar deterministic results, saving significant computational overhead. Additionally, each new cycle program statically loads each simulation program. From one perspective, the traffic simulation problem can be viewed as the forward problem, while the optimization problem is its inverse. The aim of the inverse problem is to find model parameters that optimize the fitness value, akin to a parameter identification problem. In this traffic model, parameters primarily refer to the program's timetable.

3.2 Design and Implementation

The control of traffic signals is delineated into two objectives: optimizing the continuity of traffic flow under conditions of smooth traffic and facilitating rapid dispersal of traffic in congested situations. Through the bird swarm optimization process outlined above, hierarchical analytic methods are employed to formulate multi-objective functions tailored to different objectives during various time intervals, followed by experimentation to optimize these functions and determine the optimal control outcomes for different objectives. The fundamental elements of urban traffic schemes encompass intersections, traffic signals, roads, driving directions, and vehicle passage routes. Traffic signals are positioned at intersections and regulate traffic flow through their signal light states and transition cycles. In this study, we consider all traffic signal states within a single cycle as valid. Throughout the optimization process using bird swarm algorithms, adherence to intersection traffic regulations as stipulated by traffic laws is maintained to prevent vehicular collision accidents.

In the context of traffic signal control problems, particles are represented as the phase times of traffic lights at each intersection in the road network. Within a network of intersections, this representation takes the form of a vector with n components, where the first, second, third components denote the phase times of traffic lights at intersection numbered 1, 2, 3, respectively, such as:

Xi= (33, 58, 80, 29, 64, 95, 24, 52, 82, 35, 64, 96)

In academic translation, the variation of phase times for each phase at the next simulation represents the velocity of the particles

Vi= (-1, -4, -5, -3, 3, 2, 0, 2, -3, -3, -6, 0)

The following pseudocode describes the implementation process of the bird swarm algorithm [7]initializeSwarm();

locateLeader(gbest);

while imaxGenerations **do**

for each particle **do**

updateVelocity()

updatePosition()

evaluate()

update(pbest)

endfor

updateLeader()

endwhile

The population parameters, including position and velocity information, are initialized in the first step. In the second step, the global best position is randomly initialized. Steps five and six involve updating the position and velocity information for each particle within the search space. The evolution of the population is obtained in step seven, along with the identification of the optimal position. Step eight involves updating the information regarding the global best point. Upon meeting the termination condition, the optimal solution is obtained. It is noteworthy that continuous evaluation of fitness values is required throughout this process, necessitating ongoing traffic simulations. Due to the technical challenges associated with integrating traffic simulations into the bird swarm algorithm, a dedicated section is included to discuss this aspect.

The bird swarm algorithm constitutes a significant component of swarm intelligence theory. It is characterized by ease of implementation and possesses a profound intellectual background, offering wide-ranging prospects for scientific research and engineering applications. Cao's research introduces the concept of multi-objective control, applying the bird swarm algorithm to the field of traffic signal control. This adaptation enhances the basic bird swarm algorithm, effectively mitigating premature convergence issues and noticeably improving its performance compared to the fundamental version.

4. Research on Genetic Algorithm-Based Adaptive Fuzzy Control for Traffic Signal Systems

Based on an analysis of the design structure of the classical fuzzy logic controller (Traditional FLC), Wang [8] discusses the application of genetic algorithms (GA) to optimize the fuzzy rule set and membership functions of the classical FLC used for urban isolated intersection traffic. The study elaborates on design principles, encoding schemes, selection of fitness functions, improvements in genetic operators, and other detailed issues. MATLAB simulations are conducted to demonstrate the effectiveness of this approach.

4.1 The Design Concept of Genetic Algorithm-Optimized Fuzzy Controllers

Due to the pivotal role of fuzzy control rule sets and membership functions in fuzzy control, both should be appropriately adjusted when the traffic conditions at an intersection change [9,10]. In such scenarios, the application of Genetic Algorithms (GA) to optimize the fuzzy rule sets and membership functions becomes crucial for adaptive adjustments. The objective is to reduce average vehicle delay, minimize the number of stops, and decrease the queue length at the intersection.

Let T be the signal cycle time at the intersection. If, during the *i-th* second of this cycle, the number of vehicles delayed in the east-west direction is denoted as *cLew* and in the north-south direction as *cLsn*, then the average intersection vehicle capacity, *Volume*, for this cycle is defined as shown in Equation (3-1).

$$\text{Volumn}=\sum_{i=1}^{T}\frac{(cLew_t+cLsn_t)}{T} \quad (3\text{-}1)$$

If the changes in the average intersection vehicle capacity over the last three consecutive signal cycles, compared to the average intersection vehicle capacity corresponding to the last time the fuzzy control rule sets or membership functions were optimized using GA, exceed a certain threshold (e.g., 30%), then an adaptive adjustment strategy utilizing GA optimization is invoked for the respective fuzzy rule sets or membership functions.

4.2 Simulation Experiment Results

Through simulation comparisons of the control effects of traditional fixed-time control, classical fuzzy control, and adaptive fuzzy control under different traffic conditions at the same intersection, the results demonstrate that the adaptive fuzzy control based on GA achieves superior performance compared to the other two methods. In fact, with the rapid urbanization process, residential communities are often located in the suburbs while people commute to work in the city center. Consequently, during peak commuting hours, traffic flow in the east-west (or north-south) direction significantly increases, resulting in a severe imbalance in traffic flow between the two directions. For instance, this situation is observed in Hangzhou, where the opening of residential areas in the west has led to a sharp increase in traffic pressure in the east-west direction during peak commuting hours. In such circumstances, the novel control method proposed in this chapter, which optimizes fuzzy subsets and membership functions using GA, is expected to play a significant role. With the widespread adoption and development of digital technology, the emergence of low-cost high-speed microcontrollers or Digital Signal Processors (DSPs) offers promising prospects for the application of the algorithm proposed in this chapter.

5. Conclusion and Future Prospects

With the rapid advancement of sensor technology, big data analytics, and artificial intelligence, adaptive signal control systems have emerged as key tools for addressing urban traffic challenges. These technologies enable systems to continuously perceive changes in traffic conditions and respond rapidly. Compared to traditional fixed-time signal control, adaptive signal control adjusts signal timing based on real-time traffic conditions, thereby improving road capacity and reducing congestion.

As urbanization accelerates and traffic congestion worsens, adaptive signal control systems will find broader applications. They will not only be deployed in urban centers but also in suburban areas, highways, and transportation hubs. Furthermore, future adaptive signal control systems will be integrated with other traffic management systems, such as Intelligent Transportation Systems, public transportation systems, and emergency response systems, to achieve more efficient, safe, and environmentally friendly traffic management. Additionally, as adaptive signal control systems become more widely adopted, related standards and regulations will gradually be refined. This will enhance system interoperability, maintainability, and reliability.

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