Research and Analysis on VMS Site Selection Based on Improved Genetic Algorithm: Postprint

Authors: Yu Lei, Ma Shengtao, Yang Jie, Kangyuan

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Abstract

With the rapid development of urban traffic, traffic congestion and accidents have become increasingly frequent. As an important component of Intelligent Transportation Systems, urban traffic guidance is imperative in its emergence and development. Variable Message Signs (VMS) are crucial tools for realizing traffic information dissemination in traffic guidance systems. To address the immature application of intelligent traffic guidance systems domestically, an improved genetic algorithm is employed to perform global optimization of VMS placement locations in road networks. Improvements are made to the encoding method and selection approach in the basic genetic algorithm, while mutation operations adopt dynamic decay mutation probability. A multi-objective optimization algorithm is utilized to unify multiple objective functions. Considering the varying degrees of influence that a VMS on a certain road segment exerts on different downstream locations, a decay influence factor is introduced. Subsequently, a complex virtual road network is used as a simulation example to conduct VMS layout verification. The results demonstrate that this method, using VMS utility and economic cost as evaluation metrics, effectively achieves optimal distribution of VMS site selection in traffic networks while accomplishing resource conservation, thereby possessing certain scientific validity and practical applicability.

Full Text

Preamble

Title: Research and Analysis of VMS Location Based on Improved Genetic Algorithm

Authors: Yu Lei, Ma Shengtao†, Yang Jie, Kang Yuan
(College of Electronics & Control Engineering, Chang' an University, Xi' an

710054, China)

Abstract: With the rapid development of urban traffic, traffic congestion and accidents occur frequently. Urban traffic guidance, as an important component of intelligent transportation systems, demands urgent development. Variable Message Signs (VMS) are crucial tools for traffic information dissemination in traffic guidance systems. Given the immaturity of intelligent traffic guidance system applications in China, this study employs an improved genetic algorithm to globally optimize VMS locations within road networks. The algorithm improves upon basic genetic algorithm encoding and selection methods, utilizes dynamic decay mutation probability for mutation operations, and applies multi-objective optimization to unify multiple objective functions. Considering that VMS on a given road segment have varying influence degrees at different downstream locations, an attenuation influence factor is introduced. Simulation tests were conducted using a complex virtual road network, with results demonstrating that the method, which uses VMS utility and economic cost as evaluation indices, effectively achieves optimal VMS distribution in traffic networks while saving resources, offering both scientific validity and practical applicability.

Keywords: intelligent transportation; VMS optimal layout; genetic algorithm; road network; traffic guidance

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0 Introduction

Traffic guidance systems constitute a vital component of intelligent transportation systems, significantly enhancing urban traffic efficiency. Variable Message Signs (VMS) serve as important tools for public information service in traffic guidance systems. As a collective guidance information dissemination system, their layout and information release critically impact travel quality. Determining optimal VMS distribution locations to maximize their effectiveness has become a key research topic in urban transportation. The ultimate goal of VMS deployment is to provide optimal information for drivers' route selection, though this process is subject to various subjective and objective factors, including driver response to VMS, varying effectiveness under accident and non-accident conditions, and specific installation locations at intersections.

Currently, VMS have been widely applied in developed cities worldwide, yet most deployments rely on traffic managers' experience. Research on VMS has primarily focused on logical control, display content, and driver route selection, with limited studies on placement methodologies and specific implementation schemes. Abbas [1] was among the earliest researchers to address VMS location optimization, minimizing vehicle delays by having drivers divert to alternative routes upon receiving VMS traffic information. Gan et al. [2] employed bi-level programming to determine optimal VMS locations, considering accident-prone road sections and driver response to maximize VMS benefits. Chiu et al. [3] used a bi-level stochastic integer programming model, with the upper level describing the optimal location problem and the lower level modeling driver route choice allocation. Boyles et al. [4] studied highway VMS location optimization using adaptive path search methods, considering deployment costs and guidance benefits. Fu et al. [5] calculated delay reductions for all vehicles in the network, proposing a dynamic traffic queue delay model to evaluate VMS deployment effectiveness.

Domestically, Ni Fujian and Liu Zhichao [6] applied genetic algorithms to VMS location analysis to address the complexity of integer programming models. Shang Huayan et al. [7] used a cellular transmission model to determine VMS locations by observing changes in total vehicle travel time when VMS were placed in different cells. Ji Xiaofeng et al. [8] established a VMS location method using traffic flow and information volume within VMS influence areas as effectiveness measures, quantifying risk in uncertain decisions through travel time expectation and standard deviation. Si Bingfeng et al. [9] proposed a VMS location algorithm considering both static and dynamic traffic characteristics, employing backtracking to multi-level screen road sections based on four fundamental guidance features: road hierarchy, traffic flow, deployment effectiveness, and information overlay degree. Gao He et al. [10] combined road network modification with information paths, proposing a VMS location method for one-way traffic micro-circulation and comparing results using VISSIM simulation software.

Existing VMS location research primarily focuses on location optimization without considering economic costs. This paper addresses the conflicting objectives of maximizing VMS layout effectiveness and minimizing economic costs, the complexity of bi-level programming models, and the need for a systematic optimization process for VMS deployment that enables rapid global optimal search. Based on the fundamental genetic algorithm, this study employs an improved genetic algorithm for global VMS optimization, using maximum VMS utility and minimum cost as dual objective functions to solve this nonlinear optimization problem and determine optimal layout locations.

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1 VMS Location Mathematical Optimization Model

VMS location optimization requires both maximum effectiveness and minimum manufacturing cost—conflicting objectives that demand optimal design solutions. This paper employs multi-objective optimization, converting multiple objective functions into a single objective function due to the model' s specific characteristics.

1.1 Road Network Effective Path Planning

Urban traffic networks feature high density, numerous intersections with small spacing, and many parallel road sections. For VMS location in such networks, Origin-Destination (OD) pairs must first be identified as vehicle entry and exit points. Since a network may contain many such points, effective planning paths are needed for balanced traffic flow distribution. An effective planning path is defined as the shortest-distance route between an OD pair that is relatively smooth (with relatively low traffic flow) among parallel sections. Such effective paths have lower traffic flow, reduced road load, and higher operational efficiency, effectively diverting traffic from congested sections and alleviating network-wide pressure.

1.2 Optimization Mathematical Model Establishment

VMS deployment principles aim to maximize guidance effectiveness at minimum cost. This paper makes the following assumptions: (1) Only drivers who see VMS are effectively influenced; (2) VMS are only deployed on road sections.

The influence degree of a VMS on road section a for travelers on path r can be modeled as:

$$\beta_{ra} = \sum_{i \in S_{ra}} q_i$$

where S_{ra} is the set of effective influence road sections for VMS on section a regarding path r; q_i is the frequency of incidents on section i during a period; and β_{ra} represents the benefit of VMS on section a for effective path r.

The total utility f_r^* of VMS on effective path r is the sum of utilities of each VMS on its independent effective influence section set:

$$f_r^* = \sum_{a \in A_r} F_{ra}^* = \sum_{a \in A_r} \beta_{ra} \cdot f_r$$

where f_r is the traffic flow on effective path r.

The total utility F^* for all effective paths in the network is:

$$F^* = \sum_{r \in R} \sum_{a \in A_r} \sum_{k \in B_{ra}} F_{ra}^* = \sum_{r \in R} \sum_{a \in A_r} \sum_{k \in B_{ra}} \beta_{ra} \cdot f_r$$

where R is the set of all paths; A_r is the set of all sections on path r; A is the set of all sections; B_{ra} is the remaining section set after removing the next VMS' s effective influence sections from the current VMS' s effective influence sections on path r.

Assuming C is the total VMS cost, U is the economic cost to build one VMS, and Z_a is a constraint variable where $Z_a = 1$ indicates a VMS on section a and $Z_a = 0$ indicates no VMS. The construction cost is:

$$C = \sum_{a \in A} U \cdot Z_a$$

where $Z_a \in \{0, 1\}$ for all $a \in A$, and m is the number of VMS with $M_{\min} \leq m \leq M_{\max}$.

The multi-objective optimization model is:

$$H = \frac{F^*}{C} = \frac{\sum_{r \in R} \sum_{a \in A_r} \sum_{k \in B_{ra}} \beta_{ra} \cdot f_r}{\sum_{a \in A} U \cdot Z_a}$$

1.4 VMS Attenuation Influence Factor Improvement

The above model assumes a VMS on a road section has equal and constant influence on all downstream sections. In reality, the validity of traffic information varies with distance from the VMS—traffic events farther from the VMS may change before vehicles reach them. Therefore, an attenuation influence factor e_{rak} is introduced to represent the attenuation effect of traffic information on path r, section a, displayed on VMS at section k. This paper uses an exponential function to measure attenuation degree, where influence decays exponentially for each section farther from the VMS (assuming uniform section lengths). The final objective function model is:

$$H = \frac{\sum_{r \in R} \sum_{a \in A_r} \sum_{k \in B_{ra}} \beta_{ra} \cdot f_r \cdot e_{rak}}{\sum_{a \in A} U \cdot Z_a}$$

2 Improved Genetic Algorithm

Based on the established model, VMS location optimization is a nonlinear problem requiring global search. While bi-level programming models [11] can optimize VMS layout, they are complex to implement. Immune optimization algorithms can find global optima but are inefficient and primarily target multi-peak function search [12]. Therefore, this paper employs an improved genetic algorithm for stochastic optimization search, which can jump out of local optima to quickly find global solutions.

a) Since the final objective function model H is nonnegative, single-valued, continuous, and maximizable, with relatively small computational requirements and strong generality, the objective function H is directly used as the fitness function $Fit(H)$. Given population size $N = 100$, crossover probability $P_c = 0.5$, and mutation probability P_m, when P_m is very small, population stability is good but may trap the algorithm in local optima. When P_m is large, it may disrupt population homogeneity, making performance similar to random search. This paper adopts dynamic exponential decay mutation probability $P_m = 10 \cdot e^{-x}$ where $x \in (3, 1.5)$, and sets maximum iterations $G = 100$.

b) The road network is represented by sections $a \in A$. $Z_a = 0$ indicates no VMS on section a, while $Z_a = 1$ indicates VMS deployment. Therefore, an individual is represented by a 0-1 string indicating VMS presence across all sections. Twenty such individuals are randomly generated to form population S_1, satisfying:

$$\sum_{a \in A} Z_a = m, \quad M_{\min} \leq m \leq M_{\max}$$

Set iteration counter $t = 1$.

c) Calculate fitness $Fit(H)$ for each individual in population S_1.

d) Selection: Combine roulette wheel selection with elitist preservation. Based on individual fitness, the best individual is copied intact to the next generation, ensuring the highest-fitness individual from all generations is obtained upon algorithm termination, producing population S_2.

e) Crossover: Pair individuals from S_2 for two-point crossover, where two crossover points are randomly set and paired individuals exchange segments between these points, producing population S_3.

f) Mutation: Based on binary encoding, perform bit-flip mutation with dynamic decay probability $P_m = 10 \cdot e^{-x}$ where $x \in (3, 1.5)$, producing population S_4.

g) Set population S_4 as the new generation population S_1. If termination criteria $t \geq G$ are met, stop; otherwise, increment t and return to step c).

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3 Simulation Analysis

As shown in [Figure 1: see original paper], a complex virtual road network contains 18 nodes and 36 sections. Assuming VMS are deployed on sections and their influence on downstream sections decays exponentially (independent of section length), sections 1, 5, 8, and 13 are designated as entry points, while sections 4, 8, 13, and 18 are attraction sources. These entries and attractions form OD pairs with path flows shown in . Using the proportional assignment method, section traffic flows and influence factors are obtained as shown in .

This study addresses a dual-objective optimization problem considering both maximum VMS effectiveness and economic cost. The number of VMS is set between 3 and 6, with single VMS cost assumed as 100 for computational convenience. MATLAB implementation of the improved genetic algorithm was used with VMS count set to 3. The fitness function value after 50 iterations is shown in [Figure 2: see original paper].

Additional iterations were performed for VMS counts of 4, 5, and 6, yielding optimal deployment sections shown in .

**** Path flows (thousand vehicles/hour)
**** Section flows (thousand vehicles/hour) and influence factors
**** Fitness values and optimal deployment sections for different VMS counts

VMS Count	Fitness Value	Optimal Sections
3		5, 8, 13
4		1, 5, 8, 13
5		1, 5, 8, 10, 13
6		1, 5, 8, 10, 13, 20

Results indicate that maximum fitness occurs with 4 VMS. Fitness decreases with 5 and 6 VMS because the dual-objective problem is converted to a single-objective maximization, where increased VMS count reduces the fitness function. The optimal sections reveal that VMS should be placed on high-traffic sections upstream of various paths. With 3 VMS, sections 5, 8, and 13 (near high-traffic roads) provide effective guidance. With 4 VMS, adding section 1 effectively guides vehicles passing through it. With 5 and 6 VMS, the attenuation effect of VMS information downstream necessitates additional VMS to re-induce traffic flow.

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4 Conclusion

This paper studied VMS location optimization using an improved genetic algorithm with dual objectives of maximum VMS utility and minimum cost, validated through simulation on a virtual complex road network. Results demonstrate that VMS should first be deployed on high-traffic sections upstream of paths. Considering the attenuating effectiveness of VMS information with distance, redeployment on information-intensive sections is necessary for optimal layout. The improved genetic algorithm rapidly and globally identifies optimal VMS locations, avoiding local optima limitations and demonstrating practical application value.

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Note: Figure translations are in progress. See original paper for figures.