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粒子群最適化を利用した道路ネットワークの系統信号制御のシミュレーション評価手法

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隣接交差点間における系統信号制御には多くの利点があり，その中でも最も 大きな利点は旅行時間と排気ガスの減少である．系統信号制御には様々な制約条件下での多変数最適化が必要であり，過去に多くの最 適化手法が考案されている．これらの最適化手法の精度は，最適化の過程自体の精度，評価指標の精度，入力データの精度の 3 つの要素に よって決定される．実際の適用では，一般に他の要素とも関連性のある入力データが最適化手法の不確実性の大きな原因である．本研 究ではこれら 3 つの要素を分析するために，詳細な交通流データを用いて異なるオフライン最適化手法を比 較する手法を考案した．その交通流データはメソスケール交通シミュレーション（AVENUE）によって取 得することができる．まず，最適化手法のベンチマークとして，交通需要などが所与の条件下での制御手法を，粒子群最適化を用いて 算出する．これにより，様々な最適化手法はこのベンチマークと比較することができ，かつ他の最適化手法との比較も可能になる．さ らに，交通需要変動に対する最適化手法の安定性や，停止回数や平均遅れ時間といったその他の効果指標への影響も評価することがで きる．本論文では，以上の手法について説明し，粒子群最適化の信号制御への適用を示すとともに，この手法の利点を紹介する．

A methodology for the simulation based assessment of coordination strategies for signalized networks using Particle Swarm Optimization

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Abstract

The coordination of signal programs at adjacent intersections offers many advantages, the most important being that travel times and emissions can be reduced. However, coordination is a multivariate optimization problem with many constraints. Numerous optimization strategies have been devised in the past. The quality of these coordination strategies depends on three major factors: the quality of the optimization procedure itself, the performance measures it is based upon, and the quality of the input data. In real world applications, the impact of the latter factor in relation to the other factors is commonly a source of great uncertainty. To be able to analyze all three factors, a methodology has been developed to compare different offline optimization strategies using complete information of the traffic flow. The complete information is obtained by using a mesoscopic traffic flow simulation (AVENUE). To have a benchmark for a given optimization function, the best possible coordination for given conditions (traffic demand etc.) is computed using Particle Swarm Optimization (PSO). Different strategies can then be compared to this benchmark and with each other. Furthermore, the stability of the strategies under changing traffic demand and the effect on different performance indices (e.g. number of stops, average delay) can be evaluated. This article describes the methodology, expands upon Particle Swarm Optimization as a useful tool in signal control, and highlights the opportunities arising out of the chosen approach.

Keywords: *Signal control, coordination, simulation based assessment, Particle Swarm Optimization*

1 Introduction

1-1 Signal coordination in a complex setting

Traffic signals along arterials have to be coordinated to deliver the best possible performance. The coordination is achieved by offsetting the start of the cycles of adjacent intersections relative to each other or to a defined origin. Coordination is particularly difficult to achieve on mixed traffic corridors. The required offset for adjacent signals depends not only on the intersection spacing and the cycle time, but also on the progression speed. For acceptance reasons, this progression speed should be near the average desired speed of the travelers. In consequence, requirements for passenger cars, public transport, cyclists, and pedestrians differ. Commonly it is impossible to realize a good coordination for all travelers and all flow directions. Particularly in networks with intersecting arterials, a compromise is unavoidable.

The coordination of signals, moreover, requires a unique cycle time[1]. If the traffic demand at intersections varies significantly, this unique cycle time, commonly dictated by the intersection with the largest demand, leads to inefficiencies at the intersections with less demand. In Japan, this dilemma is approached by defining “sub-areas” containing only a couple of intersections with a unique cycle time (16). At the border of the sub-areas the coordination is interrupted, but inside the sub-areas the cycle time is closer to the optimum cycle time for each individual intersection.

It is apparent that under these circumstances the definition of “best performance” is a question of policy priorities. Common optimization goals are the reduction of total delay for cars and the reduction of the total number of stops. Sometimes, for instance in Japan, a safety penalty is introduced to account for vehicles approaching during the signal change (14). Not yet of widespread use are environmental factors (emission estimates) or performance measures based on the perception of travelers as opposed to vehicle related measures, but recent research is already directed at filling this gap (3), (10), (17).

In Germany, in consequence of this complex setting the manual adjustment of the coordination based on individual and local experience of transport professionals is commonly preferred to model based optimizations following a strict performance function, which can only approximate all specific requirements (public transport prioritization, shifting traffic demand, bicycle traffic etc.).

1-2 The motivation for a systematic assessment

The overview given above underlines the difficulty in finding “the best” coordination strategy. The best strategy will depend to a large extent on individual priorities and constraints. Moreover, all existing strategies are inevita-

[1] Precisely speaking, all cycle times have to be a divisor of the greatest cycle time.

bly based on simplified assumptions, simplified traffic flow models, or limited data. Three factors influence the quality of a coordination strategy:

- the quality of the input data (be it historic data or online detected data)
- the quality of the optimization procedure itself
- the performance measures it is based upon

While in the first two areas the state of the art has reached a high level, most of even more sophisticated procedures are still based on comparably simple and inflexible performance measures (e.g. total delay). The aim of the research presented here is consequently, not to develop yet another optimization approach, but to develop a platform which can be used to compare different strategies from different points of views. This analysis is decoupled from measurement or systematic errors attending real-world applications. The outcome will be a better understanding of coordination strategies which in consequence simplifies the improvement of existing strategies or the decision for a new strategy. It, furthermore, allows for a sensitivity analysis and an estimation of the impacts of a certain strategy on performance measures not regarded in this strategy.

The methodology, a combination of a mesoscopic traffic flow simulation and a heuristic algorithm, is introduced in the next section. Section 3 expands upon the heuristic algorithm. While genetic algorithms have frequently been used for signal coordination in the past, the chosen Particle Swarm Optimization is still new in this field, but promises to get more attention in the future.

Some simple network simulations have been used to test and calibrate the model as briefly explained in Section 4. In the outlook the opportunities arising out of the methodology are outlined.

2 Methodology

2-1 Rationale

The rationale of the methodology follows the dilemma outlined in the introduction. A deeper insight into different strategies has to cover different levels:

- the variables of the strategy (e.g. offset, cycle time, sub-area definition, split)
- the performance measure (e.g. total delay, total number of stops, a combination)
- the situation (traffic flow, number of intersections, intersection spacing etc.) and the accuracy of the data hereon

The principle of the methodology is illustrated in Figure 1. While the simulation provides the performance of a network for given signal control parameters and a defined situation (traffic demand) based on complete information on the traffic flow, the signal program optimization tool improves selected signal control parameters following the strategy under scrutiny. The impact of changes in the strategy or changes in the situation can thus be traced and analyzed. To evaluate a strategy, it is conducive to know the best possible performance of a strategy, complete information provided. This benchmark is computed by the Signal Program Optimization Tool using Particle Swarm Optimization, as will be explained in Section 3.

2-2 Software concept

The Signal Program Optimization Tool (SigOpT) was implemented in C++ and docked to the mesoscopic traffic flow simulation AVENUE, developed at the Traffic Engineering Lab of the University of Tokyo. Due to the modular structure of SigOpT, the adjustment to a different simulator or changes in the heuristic algorithm are facilitated, thus improving the flexibility of the tool. AVENUE is based on a block-density model, which updates vehicle flows according to the fundamental principles of traffic flow. The traffic flow is, thus, simulated on a mesoscopic level.

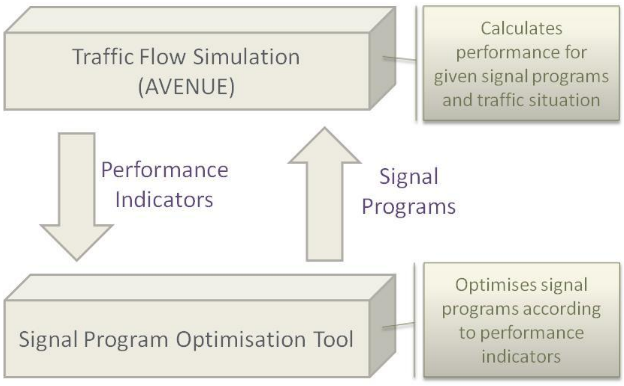

Figure 1 Illustration of methodology

3 Heuristic algorithm

3-1 Choice of the algorithm

The aim of the heuristic algorithm is to find the best possible solution for a well defined situation and coordination strategy. The challenge of the presented problem is the unknown and irregular form of the performance function, possibly containing several minima. Evolutionary algorithms like Genetic Algorithms (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO) appear to be promising approaches to solve the problem.[2]

All three mentioned algorithms are derived from natural processes and use an iterative process of generating random solutions, assessing them for their fitness, and breed a new generation of solutions based on the results of the last generation. The major difference has to be seen in the information exchange between solutions and generations. GA exchange information mutually between solutions (chromosomes). SA searches in an explorative (random) way in the beginning and limits the acceptance of newly generated solutions increasingly to solutions near the found optima (annealing). PSO exchanges information only in one direction (from the individual or swarm optimum).

While GA are used in signal control for some years already (e.g. (4) , (5), (8), (9), (18)), PSO and SA are still new to the field of signal control. Only Wang et al. (19) developed a coordination strategy using PSO for the signal program optimization. However, the objective of most of these approaches is to optimize signal programs under real world limitations, i.e. they require a simplified traffic flow model to compensate for limited data availability, or they are limited to individual intersection control.

Comparative studies of the different optimization algorithms from related engineering disciplines showed a superior performance of GA and PSO to SA (cf. e.g. (7), (13)). Almasri (1) concluded that a parallel GA has difficulties in finding the global optimum for a signal coordination problem, while a sequential GA performs well if set up suitably according to the given traffic demand.

Because PSO has proven to be a robust and capable algorithm for multi-variate optimization problems, to avoid the dilemma of having to adjust the algorithm to specific problems, and to assess the opportunities of PSO in the context of signal control, a PSO approach was chosen for the presented research.

3-2 Description of Particle Swarm Optimization for signal control

Particle Swarm Optimization algorithms are originally derived from the behavior of social animals moving synchronously in large groups (e.g. flock of birds, school of fish). The algorithm was first described and used for optimization purposes by Kennedy and Eberhart

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[2] For a short overview and introduction to nature inspired algorithms refer e.g. to (2) or (15).

in 1995 (6). Since then the algorithm evolved and several variants are used to date. While this optimization technique draws increasing attention in the research society in general, it is still new in the field of traffic engineering.

A PSO algorithm consists of a population (swarm) of particles. Each particle has a position and a velocity. For each position in the solution space a fitness can be calculated. As for all evolutionary algorithms, after the (e.g. random) generation of an initial population (positions and velocities for all particles), the fitness of each member of the population is computed, and the population is regenerated according to certain principles. In case of the PSO, each particle moves according to its individual velocity to a new position, and the velocity of each particle is subsequently updated.

The solution space is determined by the signal control parameters which are optimized. Each dimension of the solution space represents one variable. The position of the particles is, hence, defined by a vector containing values for the signal control parameters under scrutiny (e.g. offsets, splits, cycle times, sub-area assignment of intersections). If the offsets of a network of five intersections, for instance, are analyzed, four offsets can be changed. The solution space has in this case four dimensions and is limited by the cycle times.

The fitness is defined by a chosen performance measure, for instance total vehicle delay. Signal coordination strategies base their optimization on assumptions or simplified models. To avoid the error thus introduced, here the fitness is derived from a traffic flow simulation.

The size of the swarm can be freely chosen. The bigger the swarm, the more signal control parameter combinations are evaluated at the same time and the more likely the best global solution will be found. A bigger swarm requires, however, more computing time.

3-3 Tuning of the PSO

The PSO can be tuned by adjustments to the velocity update equation. The velocity (v) equation for the Constriction PSO, as the PSO variant chosen for the presented research, is given in Eq. 1. χ is the constriction factor (a function of a convergence factor and the social and cognitive factors ϕ_1 and ϕ_2), ϕ are factors determining the social and cognitive behavior of the swarm, an influence varying randomly around a given weight. Δx depicts the difference between the current position of the particle and the best position found so far (by the article itself, locally, and the swarm, globally).

$$v_{i+1} = \chi\left(v_i + \phi_1 \Delta x_{local} + \phi_2 \Delta x_{global}\right) \qquad (1)$$

The parameters ϕ_1 and ϕ_2 define the cognitive and social behavior of the particles respectively (influence by the personal or the swarm's best solution found so far). χ (constriction factor, a function of a convergence factor and the factors ϕ_1 and ϕ_2) influences the inertia of the particles (how rapidly the particles can change their velocity). While the basic PSO considers the best solution of *all* particles, it is possible for particles to consider only their neighborhood (which can be defined in different ways). Here a global search is chosen. Because it is possible that particles will leave the valid solution space, the behavior at the borders has to be considered. In addition to these tuning factors, the swarm size has a significant impact on the convergence of the algorithm.

For problems involving several equally good solutions different approaches have been proposed (11), (12). The same applies to multi-objective optimization with different Pareto-optimal solutions (20). The flexibility of PSO to deal with this kind of problems makes it particularly appealing for signal coordination, where different combinations of signal program parameters may lead to a similar performance and several performance measures have to be considered.

4 Calibration

The Particle Swarm Optimization algorithm was tested on a four intersection corridor. The total delay was used as the performance measure and the offsets as the independent variables. The dimension of the solution space was, thus, three. For this scenario, the solutions could be easily evaluated for plausibility and compared to a conservative green band optimization. This scenario was run with different PSO settings (swarm size, number of iterations, convergence parameter, boundary behavior).

A big swarm (at least about 50 particles) with a high convergence parameter (0.8) converges already after 20-30 iterations towards the best solution. For smaller swarm sizes, a lower convergence parameter is needed to find the best solution, and more iterations are needed (>50). A big swarm with high convergence parameter proved to be more efficient. Furthermore, different boundary behavior has been tested. The performance for offset optimization changed only marginally.

While an explorative swarm finds the area of the best solution fast, it tends to miss the exact optimum. This drawback can be tackled, for instance, by repeating the optimization with a greater weight on cognitive behavior and with presetting the starting position of the particles near the known near-optimum solution. Also the maximum velocity could be reduced to force a local search. Or the simple PSO could be used with a low inertia.

Figure 2 shows the statistics of an example optimization. The fitness (total delay of all vehicles in the network, one hour simulation time; 50 particles; convergence parameter 0.8; equally social and cognitive behavior) is shown on the ordinate, the iteration on the abscissa.

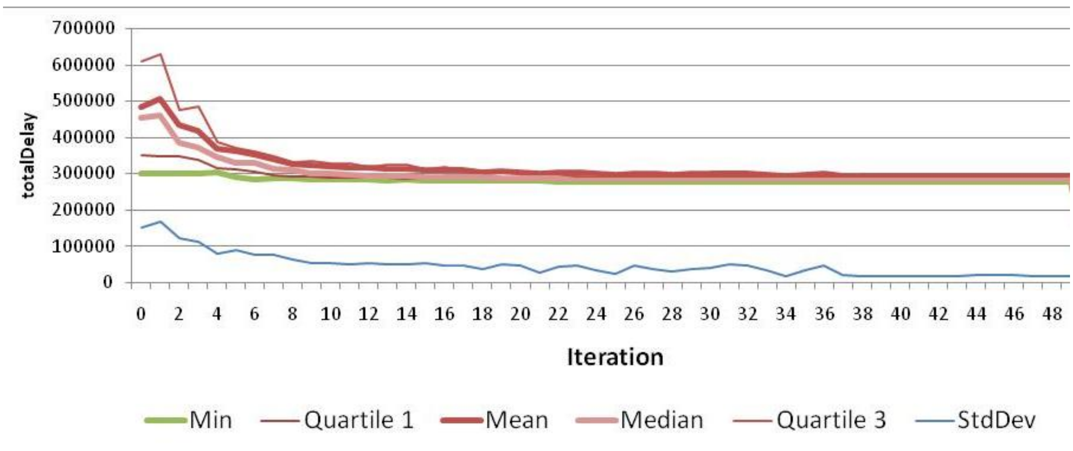

Figure 2 PSO statistics (total delay in seconds)

This simple calibration example underlines the suitability of the Particle Swarm Optimization for the analysis of signal control settings. By combining the PSO with a traffic flow simulation, the quality of the signal control settings can be judged objectively without having to consider influences by erroneous traffic data. The big advantage of PSO is, that the behavior of the particles is easy to comprehend. The different tuning parameters have a clear purpose. The calibration is, thus, no black box. It is a simple algorithm and yet very efficient.

5 Conclusions and outlook

This article describes a platform for the assessment of signal control strategies in networks. The objective is to gain a deeper insight into the behavior of existing or conceivable strategies. While in the early days of signal coordination the reduction of the delay of vehicles was the primary goal, nowadays environmental aspects and the requirements of public transport, pedestrians, and bicycles gets increasing attention. On the one hand a simplified mono-objective optimization, as it is in the core of many current coordination tools, cannot fulfill these requirements. On the other hand, with an increasing number of objectives, a mathematical optimization becomes more and more difficult. The more important it is, to understand the impacts of coordination strategies on different objectives under various conditions.

The presented methodology provides the means for this kind of analysis. The methodology consists of a combination of a heuristic algorithm as the optimization tool, and a traffic flow simulation (in this case AVENUE), to provide the true performance of a given network. Particle Swarm Optimization has proven to be a simple and yet versatile and efficient algorithm to find the best solution for given conditions. Even in its basic form it converges fast to a near-optimum solution.

While for the proof of applicability and the calibration of the presented methodology a simplified network was used, more realistic networks will be employed in the future application. Thus different real world settings can be assessed. The focus will be on different performance measures (e.g. number of stops vs. delay, weighting of routes etc.), different network layouts (intersection spacing, traffic volumes etc.), and different optimization parameters (cycle times, sub-area assignment, offsets, split).

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