Design optimal ITS Systems Using Simulation-based Optimization and Retrospective Approximation Techniques

---A New Framework of designing cost-effective ITS systems

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ABSTRACT

Intelligent Transportation Systems (ITS) is considered as an effective tool to improve the level of traffic services. It integrates the newly emerged IT technologies with the traditional traffic engineering. By providing the traffic partners with better communications, ITS can significantly boost the traffic managements and operations. Meanwhile, however, the deployment of the ITS applications often involve a huge amount of investments, which may be discouraging in a challenging economy like now. Therefore how to increase the cost-effectiveness of the ITS systems is a widely concerting issue.

There has been limited research efforts on the optimization of the ITS systems. The introduction of IT technologies increases the complexity of the traffic systems and therefore many model-based optimal traffic designs become questionable in the scheme of ITS. As a result, most ITS systems can be only investigated through the simulation-based methods. The optimization of the ITS systems can be classified as the problem of "simulation-based optimization" (SO).

Traditionally, the simulation-based optimization is first to approximate the unknown systems by sampling and averaging the simulations then apply the optimization algorithms. Its weakness is that it may expend excessive optimizing efforts in the beginning to understand the properties of the ITS systems and thus it may take long time to reach the optimal designs. The Retrospective Approximation (RA) represents the latest development of simulation-based optimization and it is a generic technique to solve SO problems. Unlike the traditional SO methods, the optimal ITS designs can be approached by using a sequence of approximate optimization problems. These

approximate problems are generated with increasing sample sizes and solved to decreasing error tolerances. In the early RA iterations, the system approximations are not close to the true system due to their small sample sizes. They are mainly used to better understand the system. The large error tolerance can prevent the optimization algorithms from expending excessively search efforts. With the sample size increasing, the approximate systems will gradually approach the true system and a smaller error tolerance will ensure the precision of the optimal ITS designs. In this essay, we first describe in detail how the RA techniques can be applied to designing the optimal ITS systems; secondly we develop the prototype of the RA-based optimization engine using VISSIM and VC++; lastly we discuss the potential applications of the new framework for ITS Systems Designs.

INTRODUCTION

The traditional optimization methodology for the traffic systems often replies on the analytical models. It is questionable due to the facts as follows:

(1) The traditional methodology often ignores driving behaviors (e.g., car following, lane changing). However, these "trivial" driving behaviors turned out to be decisive in many cases.

(2) Many traditional optimization algorithms were designed to optimize deterministic problems and therefore they cannot tackle the inherent randomness in the traffic systems. As a result, the solutions suggested by the traditional optimization algorithms cannot answer such questions as "how robust is the optimal solution?" or "How much likelihood will the optimal solution fail if something unexpected occurs".

The purpose of this essay is to address these two issues by introducing the retrospective approximation technique into the optimal ITS design. We structure this paper into 4 parts: in the first part, we review the applications of the stochastic optimization and the retrospective approximation techniques; in the second part, we analyze the major issues residing in the latest practice of the optimization of traffic systems; in the third part, we described an optimization engine based on the traffic simulation package, VISSIM, and the RA technique; in the last part, we discuss the possible applications of this new engine.

LITERATURE REVIEW

Stochastic optimization methods, also called stochastic root-finding methods in other literature, are a family of optimization algorithms which incorporate random elements either in the problem structure (objective function, constraints, etc) or in the algorithms itself (random choice of parameters, etc). There are two major issues in the stochastic optimization issues: (1) how to approximate a stochastic system that can only be observed with random errors; (2) how to search statistically optimal solutions to the random but observable systems by using algorithms with statistical features.

Sample Average Approximation (SAA) is a traditional technique to solve stochastic optimization problems. The SAA technique was first suggested by Healy and Schruben (*1)* and later referred to by Rubinstein and Shapiro (*2)* and Shapiro and Homem-de-Mello (*3)* to solve stochastic optimization problems. The idea of SAA is straightforward: since the actual simulated-based optimization is difficult to solve, we may solve an approximate problem *S* obtained by substituting the true (also unknown) objective function *G(x)* by the sampled approximation $\overline{y}_m(x;\underline{\omega})$. $\overline{y}_m(x;\underline{\omega})$ is the realization of the unbiased estimator $\overline{Y}_m(x)$ of $G(x)$ and $\overline{y}_m(x;\underline{\omega})$ is generated using the vector of random numbers $\underline{\omega} = \{\omega_1, \omega_2, ..., \omega_m\}$ and sample size *m*. In light of SAA, instead of optimizing the original stochastic problem (*G*), the approximate deterministic problem (*S*) generated with a large sample size can be solved to optimality with proper optimization algorithms. The solution to *S* will converge to the solution to *G* with probability 1 when $m \to \infty$.

Retrospective Approximation (RA), proposed by Chen and Schmeiser (*4),* is a variant of SAA. Later on, Pasupathy and Schmeiser extended the RA technique (*5)* to multiple dimensions and Pasupathy investigated how to make the RA algorithm converge fast (*6)*. RA reflects the latest development of the simulation-based optimization. Instead of generating a single approximate function *S*, a sequence of approximate functions $\{S_i\}$ are generated with increasing sample sizes $\{m_k\} \to \infty$, and solved to decreasing tolerances $\{\varepsilon_k\} \to 0$. The underlying rationale is that in the early iterations, the approximate objective functions $\{S_i\}$ are not very close to the true objective function *G* due to their small sample sizes. Therefore, the optimization in early iterations is primarily to better understand the problem. For instance, with certain heuristic searching algorithms, the optimum in the early iteration may be used as the initial guess for the next iteration. This measure, consequently, can increase the chance to obtain the global optimum in the next iteration.

The small sample size and large error tolerance can ensure the early iterations will not expend excessive efforts. With the sample size increasing, it is necessary to lower the error tolerance so that the sample path of the optimal solutions in all iterations can gradually approach the true optimum with probability one (Fig. 1).

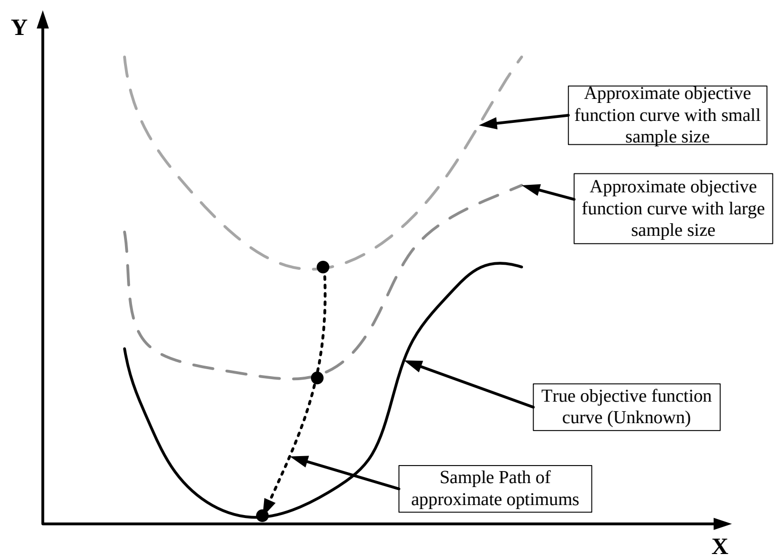

Figure 1 conceptual illustration of the RA technique

The iterations continue until the preset stopping criteria are satisfied. It is also worth noting that the RA framework is generic and therefore we have the flexibility of selecting the appropriate algorithms according to the problem.

PROBLEM STATEMENT

The loss of driving behavior in the analytical model has been well addressed in previous studies. The latest research efforts can directly connect the commercial traffic simulation packages, which can mimic vehicles' various driving behaviors, with the optimization algorithms. Nevertheless, the converging rate of the stochastic optimization has been a major issue in practice. For example, the commonly used genetic algorithm requires a huge amount of time to obtain the "acceptable" solution. When dealing with large-scale ITS systems, the required computing time may be too long to afford. To address this issue, the state-of-practice methods either used small sample sizes, such as five repetitions, to approximate the objective function or decreased the population size/generations. Although these measures can help maintain an acceptable computing time, the globality and unbiasness of the solutions may be compromised.

We address these issues by applying the latest RA technique to the optimization of the ITS systems. The RA technique provides a mechanism to conduct the robust analysis as well as the flexibility of designing/adjusting proper optimization algorithms that converges fast.

ALGORITHM DESCRIPTION

In light of the RA technique, the optimization algorithms can be selected according to the problem properties. The proposed optimization algorithm in this section is designed by the author. The readers can definitely either expand this algorithm or design their own optimization algorithm following the same procedure.

Initialization: the sample size and error tolerance for the first iteration are set as $m_1 = 1$ and

$$\varepsilon_1 = \frac{1}{\sqrt{m_1}}.$$

Rules for successive increasing sample size and decreasing error tolerance:

$m_i = RoundUp\left[(1+10\%)m_{i-1}\right](i \geq 2)$ and $\varepsilon_i = \frac{1}{\sqrt{m_i}}$.

The simulated annealing algorithm: the *simulated annealing* algorithm (SA) is a global optimization algorithm based on random search in the state space (*7)* and it is used to obtain the optimum in each RA iteration. Each step of the SA algorithm replaces the current solution by the best random "nearby" solution, which is selected with the probability proportionally to a global parameter T (“temperature”) and the difference between the corresponding objective function values. T is gradually decreased during the process. When T is large, the current solution may change almost randomly. However, when T keeps decreasing to zero, the new solution will approach the local optimum with certainty.

Now we are ready to describe the RA-based stochastic optimizaiton method, which is shown in Fig.2.

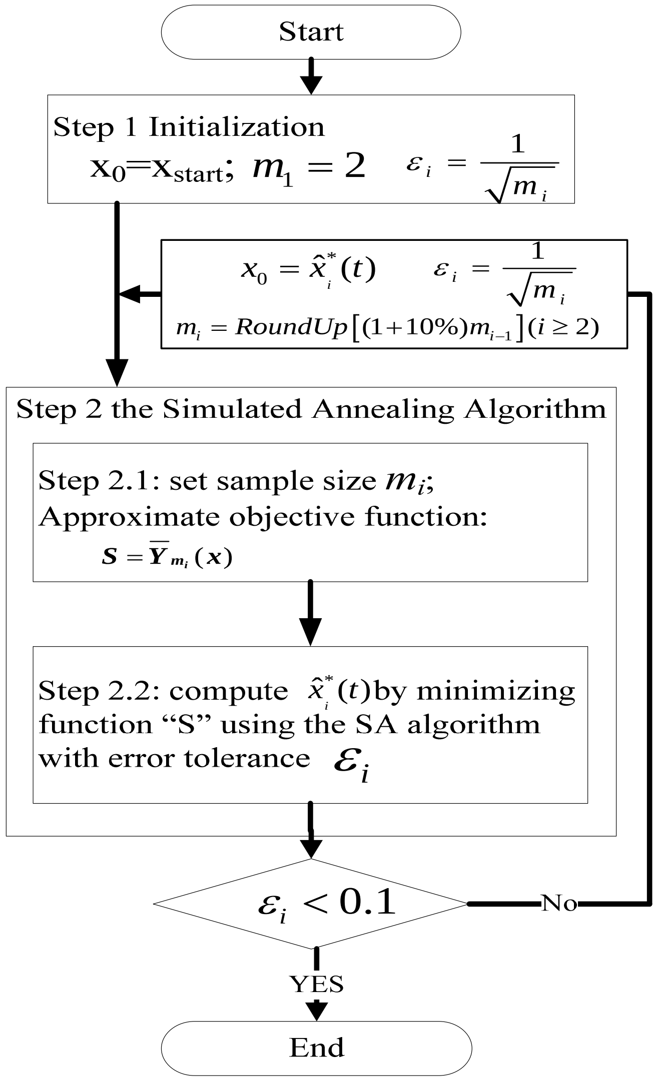

Figure 2 Flowchart of the RA-based stochastic optimization

THE RA-BASED OPTIMIZATION ENGINE USING VISSIM

We developed the prototype program of the RA-based optimization engine in light of the new framework. In this program, we coupled the RA-based optimization algorithm with a commercial microscopic traffic simulation environment, VISSIM (*8)*. The optimization algorithm sends each candidate solution into VISSIM then drive the simulation via VISSIM COM. After each simulation run, the output is sent back to the optimization algorithm. Then the optimizing algorithm will determine the search direction accordingly. Fig. 3 illustrates the VISSIM-based stochastic optimization.

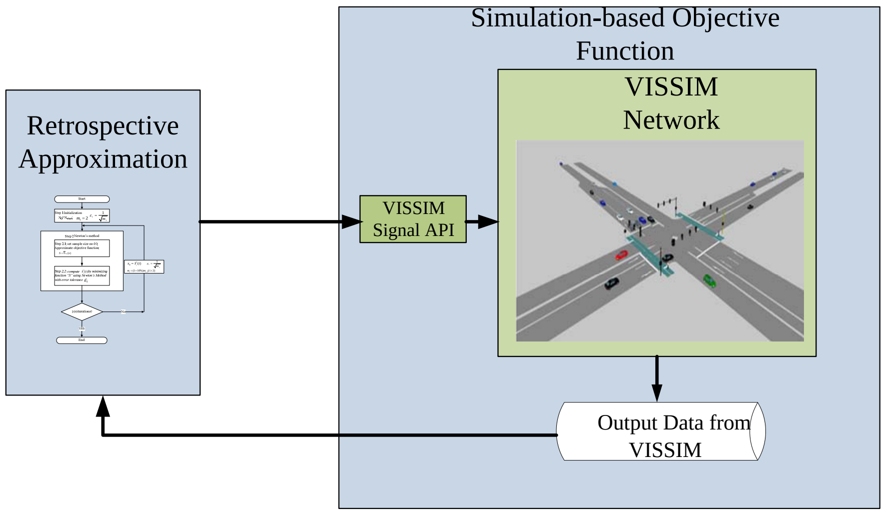

Figure 3 illustration of the VISSIM-based optimization

DISCUSSION AND FUTURE WORK

There are many potential applications of this new framework. Taken as examples, this new framework can be used to optimize the signal control systems in the Advance Transportation Management Systems (ATMS); it can also used to determine the best transit preemption plans in the Advance Public Transit Systems (APTS) and it can also be used to design the optimal configurations of the changeable message boards in the Advance Travelers Information Systems (ATIS).

In a long term, we also plan to apply this new VISSIM-based optimization engine to the large-scale ITS designs and plan to develop the concept of "ITS-in-the-loop" simulation environment, in which the simulation engine will be coupled with the ITS applications.

REFERENCE

1. Healy, K. and L.W. Schruben. *Retrospective Simulation Response Optimization*. in *Proceedings of the 1991 Winter Simulation Conference*. 1991. Piscataway, New Jersey: IEEE.
2. Rubinstein, R.Y. and A. Shapiro, *Discrete Event Systems: Sensitivity Analysis and Stochastic Optimization by the Score Function Method*. 1993, New York: John Wiley & Sons.
3. Shapiro, A. and T. Homem-de-Mello, *A Simulation-based approach to two-stage stochastic programming with recourse.* . in Mathematical Programming, 1997. 81: p. 301-325.

4. Chen, H. and B.W. Schmeiser, *Stochastic Root Finding via Retrospective Approximation.* in Institute of Industrial Engineers Transactions, 2001. 33: p. 259-275.
5. Pasupathy, R. and B.W. Schmeiser. *Retrospective Approximation Algorithms for the Multidimensional Stochastic Root-finding Problem*. in *Proceedings of the 2004 Winter Simulation Conference*. 2004. Washington, DC, USA.
6. Pasupathy, R. *On Choosing Parameters In Retrospective-Approximation Algorithms for Simulation-optimization*. in *Proceedings of the 2006 Winter Simulation Conference*. 2006. Monterey, CA.
7. Emile, A. and K. Jan, *Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing*. 1991.
8. PTV-AG, *VISSIM 5.10 User Manual*. 2008. p. 438.