Optimization of Time of Day Plan Scheduling Using a Multi-Objective Evolutionary Algorithm

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Optimization of Time of Day Plan Scheduling Using a Multi-Objective Evolutionary Algorithm

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ABSTRACT

Coordinating traffic signals can provide great savings to motorists in terms of reduced delays and number of vehicular stops. In order to maximize benefits, engineers need to use a mechanism by which the most optimal timing plans are activated when the traffic patterns change. Common ways of accomplishing this need is by using Time of Day (TOD) plan scheduling, or Traffic Responsive Plan Selection (TRPS). Out of the two modes, the TOD mode is by far the most common. Engineers, however, typically use their judgment to determine the TOD plan scheduling. Unless traffic patterns change at certain times of the day and remain constant until the next change—which is highly unlikely—it is very difficult to determine what the optimal break point would be. In addition, engineers would also face the challenge of selecting the timing plan that would be active during every scheduling period. This paper proposes the use of a multiobjective evolutionary algorithm to address these challenges. The authors introduce the Degree of Detachment (DOD) as a performance measure of scheduling continuity. A high DOD translates into frequent changes in timing plans. Whereas a zero DOD translates into a one timing plan applied throughout the day. The authors then use a non-dominated sorting genetic algorithm (NSGAII) to optimize the TOD scheduling. This approach results in different Pareto fronts, corresponding to different DODs, where engineers can evaluate the incremental benefits associated with increasing the frequency of timing plan changes.
INTRODUCTION

Coordinating traffic signals in a closed-loop system can provide significant reductions in travel and delay times. In order to achieve signal coordination, timing plans need to be developed so that the coordinated system can work in a synchronized mode. As traffic patterns change during the day, different timing plans need to be activated to achieve optimal performance. Several studies were conducted over the years to improve the development of optimal timing plans. Computer optimization packages, such as PASSER II (1), SYNCHRO (2), and TRANSYT-7F (3), are widely used to generate optimal timing plans. However, very limited research has been conducted on the optimization of the TOD plan schedule. In addition, very limited guidance is provided on which timing plan should be implemented during a TOD period. It is inevitable that during a TOD period, traffic patterns are not constant, and every traffic pattern could be used to generate its own optimal timing plan.

In practice, traffic engineers collect data for a representative day of the week and visually decide on when there is a significant change in traffic patterns. This procedure typically results in engineers deciding on dividing the day into several periods such as am-peak, off-peak, pm-peak, etc. The engineers then proceed with using a representative traffic pattern from 15-minute counts obtained throughout each period, and design a timing plan for that pattern. The engineers then apply the resulting timing to the entire period. While this procedure is not very complicated, it usually results in sub-optimal and subjective decisions of when and which timing plans to be implemented in a coordinated system. One can wonder whether a different selection of timing plans could have resulted in better system performance. One also would not know for sure if the frequency of timing plan changes is excessive. There is a need, therefore, for some sort of a systematic procedure for the engineer to follow. While this research does not claim to answer all questions, it proposes a novel methodology to address the problem.

Past Research

As mentioned above, most of the studies about signal coordination were focused on creating better traffic signal timing plans using various optimization techniques. There is, however, a limited number of studies that looked at determining TOD break points. These studies mainly used statistical clustering techniques to arrive at the best obtainable TOD break point (4). A major limitation of the statistical clustering is the fact that clustering procedures do not take into account the “preference” of traffic engineers to minimize zigzag changes between timing plans. Statistical clustering can result in a particular timing plan activation every other 15-minute period, simply because the traffic patterns in these every other periods are having similar volumes.

Park et al. (5) used a genetic algorithm (GA) to clean out these odd clusters of traffic patterns. Their approach, however, has occasionally resulted in the creation of irrational TOD
break points (6). Another study by Park et al. used a two-steps GA to automate the process of optimizing TOD break points (6). In their approach, they used an outer loop to determine the TOD break points, and an inner loop to evaluate the performance of these break points. Their GA used the HCM delay equation as an objective function. Their approach, while promising, does not take into account the coordination effect of timing plans. In addition, the GA design itself does not guarantee the convergence of the inner loop before processing with the outer loop.

**PROPOSED APPROACH**

This paper proposes the use of a multi-objective evolutionary algorithm to address the TOD scheduling challenges. In addition to optimizing the coordinated system delay and stops, the authors introduce a new performance measure of plan scheduling continuity presented here as the Degree of Detachment (DOD). A high DOD translates into frequent changes in timing plans. Whereas a zero DOD translates into a one timing plan applied throughout the whole day. The authors then use a non-dominated sorting genetic algorithm (NSGAII [7]) to optimize the TOD scheduling such that both system delays and stops are minimized. The NSGAII produces a Pareto front where the engineer can evaluate the incremental benefits associated with increasing the frequency of timing plan changes.

**Genetic Algorithms**

GAs are optimization techniques based on the process of natural selection and genetics (8). GAs are generally used when there is no clearly defined function for solving an optimization problem, and when it is infeasible to solve the problem with complete enumeration. A GA approaches the problem by generating and evaluating a large number of random solutions. In the context of TOD scheduling, a GA generates random schedules by dividing the day into a limited number of Time periods (e.g., 96 time periods, 15 minutes each) and assigning a timing plan to each of the individual periods. Through natural selection and the genetic operators, crossover and mutation, individual solutions with better fitness are found. The crossover operator mates genes from two parent solutions to form two new children solutions that have a high probability of having better fitness than their parents. The crossover operator swaps parts of the plan assignments from the two parents. Keeping the schedule before 1 p.m., for example, intact, and switching the schedule after 1 p.m. between the two parent solutions. The mutation operator places a random plan at a random time period. This natural selection process guarantees that solutions with the best fitness will propagate in future populations. The crossover operator emphasizes the exploitation of the solution surface. While the mutation operator allows new areas of the response surface to be explored, and prevents the solution from being trapped at local minima.
Degree of Detachment

The GA procedure explained above does not account for the desire (and need) of engineers to have minimum number of timing plan transitions during the day. In fact, it is very likely that a GA will find optimal solutions that assign different timing plans to adjacent time periods. There was, therefore, a need to emphasize the continuation of a timing plan, if possible, over several timing periods before the timing plan changes. The authors defined the DOD metric for the purpose of clustering traffic patterns while accounting for the general preference of avoiding zigzag changes in timing plans. The DOD measures the degree by which a time period (or equivalently, the traffic pattern at the time period) is detached from adjacent periods in term of its assigned timing plan. In this context, detachment occurs when the adjacent traffic pattern (pattern that occurs one time period before or one time period after the current pattern's time period) is associated with a different timing plan. As such, the DOD value for a given TOD plan schedule can be calculated as:

\[
DOD = \sum_{i} (DOD_{i1} + DOD_{i2})
\]

where,

\[
DOD_{i1} = \begin{cases} 
0, & \text{if } X_{i-1} = X_i \\
1, & \text{otherwise}
\end{cases}
\]

\[
DOD_{i2} = \begin{cases} 
0, & \text{if } X_{i+1} = X_i \\
1, & \text{otherwise}
\end{cases}
\]

and, 

\[
X_i = \text{plan assigned to time period } i
\]

It can be deduced that for a 96 time periods (24 hours with 4 periods per hour), the maximum possible DOD is 190 while the minimum possible DOD is zero.

Non-Dominated Sorting Genetic Algorithm

The need to minimize both delay and stops, while trying to cluster similar timing plans together, calls for a multi-objective optimization process. The authors used the NSGAII evolutionary technique for this purpose. Unlike the traditional approach of assigning pre-defined weights to each objective function, multi-objective evolutionary algorithms strive to find the Pareto front (the front of compromised solutions) of all objectives. Figure 1a shows a conceptual Pareto front for the stops and delay in a coordinated system. Solutions lying above the Pareto front are nonoptimal solutions, while those lying below the Pareto front are infeasible
solutions. All solutions on the Pareto front are optimal with regard to at least one objective. Point A, for example, corresponds to a weight of 100 percent assigned to the delay objective, and 0 percent assigned to the stops objective. Point D corresponds to a 0 percent and a 100 percent weights assigned to the delay and stops objectives, respectively. Point B corresponds to a 50 percent weight assigned to each of the two objectives. The shape of the Pareto front itself provides very valuable information to the analyst. One would know, looking at the Pareto front shape, how much other objective functions would be compromised if a selected objective function is to be favored.

Figure 1b shows the effect of including the DOD objective in the optimization process. The conceptual figure illustrates that it is expected to obtain less delay and stops if the use of schedules that contain more timing plan were allowed. The uppermost Pareto front corresponds to a zero DOD (i.e., only one timing plan is activated throughout the whole day). The timing plan itself could be selected to achieve minimum delay, stops, or some combination of the two (and hence the existence of the Pareto front). Allowing one transition during the day (i.e., a DOD of 2), translates into the ability to select two timing plan during the day. This in turn is expected to result in lower delay, stops, or a combination of the two (basically, shifting the Pareto front downwards). It is anticipated that the increase in the number of transitions allowed will soon reach a point of diminishing return with regard to the increase in benefits. It should also be noted that the increase in number of transitions is usually accompanied by an increase in transitioning cost. While this is not quantified in this paper, the incremental shift in Pareto front will give the engineer a clear idea of the amount of benefits expected from allowing (or selecting) more transitions in the TOD schedule. The engineer can then weigh that with the possible cost of transitioning.

The NSGAII is similar to simple GAs in the use of the selection, crossover, and mutation operators. However, prior to the selection step, the algorithm ranks the whole population based on all objectives. All individuals in the population that are non-dominated (i.e., there does not exist an individual TOD schedule that is better than the current individual in more than one objective) are assigned a rank of one. These individuals with rank one are removed from consideration and all other individuals are ranked again and are assigned a rank of two. The process continues until all individuals are assigned a rank. After the process is completed, a crowding distance is calculated for all individuals. The crowding distance is a metric used to diversify the population by assigning a higher fitness to individuals with larger cuboid formed by the individual and its neighboring individuals. For example, if points A, B, C, and D were the only four points in the Pareto front in Figure 1a (which is not the case), point A would have a higher crowding distance than point D since there is a larger distance to the neighboring solution of point A than that of point D. The inclusion of the crowding distance concept in the optimization insures the formulation of a Pareto front at the end of the algorithm run. Otherwise, the Pareto front might converge to a single point.

The selection operator is then applied while assigning higher fitness to individuals with
higher ranks and crowding distances. The algorithm ensures elitism by combining the parent population with the children population before the crossover and mutation operators are applied. Figure 2 shows the integrated NSGAII-DOD algorithm.

CASE STUDY

The procedure proposed in this paper is illustrated with a case study in Odem, Texas. The coordinated system consists of three intersections on US 77. The intersection layout and geometry are shown in Figure 3. Traffic data was collected in the site for 10 days using system detectors. Out of these days, Tuesday was selected as a typical day for the procedure's demonstration. Figure 4 shows traffic volume variation of each movement for the three intersections. The figure illustrate that during a typical day, large variation of volume occurs at all intersections with gradual volume increase in the morning and gradual decrease at the end of the day.

Timing Plan Generation

Odem coordinated system offered 96 volume patterns per day (data uploaded every 15 minutes) PASSER V was used to generate timing plans for each traffic pattern. Cycles used in the analysis ranged between 60 seconds to 180 seconds with 5 seconds steps. The 96 traffic patterns therefore resulted in the production of 2,400 timing plans. The 2,400 selected plans were then run with all of the 96 traffic patterns to obtain delay and total number of stops for all pattern-plan combinations. This 96 by 2,400 performance matrix was then used as an input to the NSGAII DOD algorithm.

Delay, Stops and DOD Evolution

A sensitivity analysis of the NSGAII-DOD algorithm conducted for all combinations of population size of 200 and 500, crossover probability of 0.5 and 0.8, and mutation probability of 0.01 and 0.1. The delay stops, and DOD values were plotted for all generations. Both best and worst values in a single generation were plotted for each objective function. It was found that the NSGAII-DOD produced almost the same results for all combinations. Figure 5 shows the evolution of each of the three objective functions for a population of 500, crossover probability of 0.8, and mutation of 0.01. It should be noted that the DOD improved from 190 to 0 very quickly within the first 50 generations. The algorithm was able to reduce the total number of stops from about 120,000 to 42,000 vehicular stops and the delay from about 350 to 55 veh-hrs as the number of generations increased.

The Pareto Front

As discussed earlier, one of the very nice features of the multi-objective optimization algorithms is the production of the Pareto front. The Pareto front eliminates the need for trying,
for example, different number of break points in the TOD schedule to compare results. The multi-objective optimization algorithm computes and produces the Pareto front at the end of the optimization run. Since the Pareto front shows the front of all non-dominated solutions, the engineer can select any of the solutions lying on the Pareto front without jeopardizing optimality. More importantly, one can tell exactly how much more cost is incurred on a certain objective if another objective was favored by a certain amount.

Figure 6 shows the final Pareto fronts produced by the NSGAII-DOD algorithm at the end of the optimization run. Note that the engineer can tell, looking at the figure 6a, how much reduction in total number of stops is possible with keeping low DOD Index. Figure 6b represents the inverse relationship between delay and number of stops. Figure 6c shows how much reduction in DOD Index is possible while keeping low delay. Therefore, the analyst can select a reasonable point which relatively satisfies both low delay and small number of stops at a time.

Figure 7 was obtained by sorting the output data presented in Figure 6 by DOD index. Figure 7 shows that the Pareto fronts corresponding to different DOD indices converge quickly to form almost the same curve with DOD index of 8 and more. The figure suggests that Pareto fronts with DOD index greater than 8 should not be used, as higher DOD fronts will only results in more transitioning cost without any gain in benefit. For illustration purposes, five solutions were selected from each of the five Pareto fronts as shown in Figure 7. Note that the Pareto front for zero DOD does not include a solution that favors both delay and stops equally. A solution favoring the number of stops is selected for zero DOD as a result. As the DOD value increases, more solutions with low delay and small number of stops become available. Figure 8 shows the actual timing plan schedules that correspond to the five solutions presented in Figure 7, along with the associated delay and number of stops. Table 1 shows the six timing plans used to formulate the five TOD plan schedules.

CONCLUSION

This paper proposed the use of a multi-objective evolutionary algorithm to optimize the TOD plan scheduling. The paper defined a new measure of performance (the DOD) to provide a clustering mechanism of traffic patterns. The DOD was able to provide a clustering procedure that does not suffer from drawbacks encountered by previous research methods. The paper illustrated the integration of a non-dominated sorting genetic algorithm with the DOD measure to optimize the TOD scheduling. Using sample field data from a coordinated system in Texas, the developed algorithm was able to produce five solutions that correspond to different number of allowed transitions during the day. Solutions with more frequent timing plan transitions exhibited lower delay and number of stops. However, it was found that no significant benefits were obtained for allowing more than four transitions in the day for this specific system.
The multi-objective evolutionary algorithm with DOD was successful in finding optimal selection of timing plans as well as the optimal TOD schedule. In addition, it provided several options for the analyst to choose from. All options being optimal, but different in the preference levels they assign to each of the two objective functions, delay and number of stops. The authors therefore recommend the use of the multi-objective evolutionary algorithm to determine the TOD plan schedule.

RECOMMENDATION AND FUTURE WORK

It is recommended that the above procedure be implemented in the signal optimization programs to determine the optimal TOD schedule. It is also recommended that the cost of transitioning be integrated with the multi-objective algorithm.

REFERENCES

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c) Main Street @ US 77

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a) DOD Index = 0, Delay = 268.6 veh-hr, Stops = 44226 veh
b) DOD Index = 2, Delay = 214.2 veh-hr, Stops = 55936 veh
c) DOD Index = 4, Delay = 206.9 veh-hr, Stops = 54656 veh
d) DOD Index = 6, Delay = 205.5 veh-hr, Stops = 55246 veh
e) DOD Index = 8, Delay = 205.3 veh-hr, Stops = 55559 veh

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## Optimization of Time of Day Plan Scheduling Using a Multi-Objective Evolutionary Algorithm

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FIGURE 1 Conceptual Illustration of Pareto Fronts.
Optimization of Time of Day Plan Scheduling Using a Multi-Objective Evolutionary Algorithm

Start

Read plan-pattern performance matrix as output by PASSER V Software

Initialize first population with all assignment of timing plans to time periods

Perform GA operators to produce a new better generation

Calculate total system delay
Calculate total system number of stops
Calculate total system DOD

Rank population by delay, stops and DOD And calculate individual fitness.

Final generation?

Yes

Pareto front with optimal solutions

No

FIGURE 2 Integrated NSGAII-DOD Algorithm.
FIGURE 3 Odem Coordinated System and PASSER V Network.
Optimization of Time of Day Plan Scheduling Using a Multi-Objective Evolutionary Algorithm

![Traffic Volume Graphs](image)

a) Baylor Street @ US 77

b) Willis Street @ US 77

c) Main Street @ US 77

FIGURE 4 Traffic Variations in Odem System.
Abbas, Sharma & Jung in *Proceedings, Transportation Research Board 84* (2005)

FIGURE 5 Algorithm Convergences.
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FIGURE 6 Final Pareto Fronts.
FIGURE 7 Final Pareto Fronts Sorted by DOD Index.
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FIGURE 8 Final TOD Plan Schedule Solutions.