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Sustainable Travel Incentives Optimization in Multimodal Networks

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SUSTAINABLE TRAVEL INCENTIVES OPTIMIZATION IN MULTIMODAL NETWORKS

A Thesis Presented

by

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Hossein Ghafourian

ABSTRACT

SUSTAINABLE TRAVEL INCENTIVES OPTIMIZATION IN MULTIMODAL NETWORKS

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Tripod, an integrated bi-level transportation management system, is a smartphone application from the potential user's point of view which would be instantly accessed prior to performing the trip. Since there are constantly several alternatives for any trip, Tripod considers a series and combination of various parameters, including departure time, mode and route, and rewards for each alternative with a number of redeemable points for goods and services called "Tokens". The framework responsible for computing the *optimized* number of tokens awarded to the set of available alternatives in order to *minimize* the system-wide energy consumption under a constrained Token budget, is the System Optimization (SO) implemented in Tripod. To do so, a higher number of tokens would be awarded to the alternatives, guaranteeing a larger energy saving, less energy consumption, alternatively. SO is multimodal whereby public transit, private car, carpooling, etc. are being considered as the potential travel modes. Furthermore, SO is *dynamic, predictive* and *personalized*: the same alternative is rewarded differently, depending on the current and predicted future condition of the network and on the individual's profile. In order to solve this problem, a multimodal simulation-based optimization model will be elaborated.

Keyword: incentives, system optimization, energy, real-time optimization, prediction, personalization.

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CHAPTER 1

INTRODUCTION

The thesis research is part of a collaborative project between MIT and UMass Amherst. Team members who have contributed to the work described in the thesis are Andrea Araldo, Ravi Seshadri, Carlos Lima Azevedo, Yihang Sui, David Sukhin, and Moshe Ben-Akiva from MIT, and Sayeeda B. Ayaz from UMass. This thesis is based on [3] and [4].

1.1 Project Background

A reliable and sustainable transportation system, as an indispensable part of each society, plays a significant role in providing social welfare and prosperity. "Urban transportation networks worldwide, however, are beset by issues of excessive congestion and energy consumption, which are critical obstacles in achieving these goals." [3] Due to having limitations in increasing system capacity, travel demand management has received considerable attention as a remarkable way of utilizing the existing infrastructure in a more efficient manner. "From the real-time demand management perspective, externalities such as congestion and vehicular emissions have been historically addressed with information provision [1] or pricing strategies [2,6]." [3] As a matter of fact, congestion pricing is one of the demand management strategies that has been comprehensively researched [7,8] whereby the transportation users are supposed to pay for the "full cost of their trip, their own travel cost and those imposed on the other users due to the generated congestion. It aims at curbing excessive demand and take advantage of the transportation facilities in the most efficient and practical way. Singapore, London and Stockholm are among the few major cities over the world that have such a scheme area-wide. For example, in London, one needs to pay 11.50 £ to drive a personal vehicle within Central London between 7am and 6pm, with more polluting cars paying more." [3] There are some critical rationales regarding the congestion pricing which lead to general aversion and equity concerns, benefiting the high income via preventing the low-income travelers from using some facilities because of being charged.

1.2 State of Practice and State of art

Since the basic and influential paper by Pigou [9], road pricing gained remarkable attention from the theory stage to the actual implementation. In terms of congested networks, in order to improve road network performance and increase its serviceability, various mathematical models and algorithms have been developed in favor of toll optimization (refer to Lindsey et al. [7] and Tsekeris et al. [8] for a more comprehensive understanding). Regarding the pricing strategies, dynamic pricing, as one of the recently persuasive strategies, were greatly studied. One of the pioneering studies in this field was that of Gallego et al. [10] in which optimization formulation and a proposed solution through maximizing revenue under stochastic and aggregated demand was introduced. Although several frameworks have been proposed subsequently, few actual implementations have been tested. Moreover, travelers' attitude toward road pricing, how they perceive it as an unfair additional cost or another tax, is of great importance. However, equity is discerned as an important factor in the pricing strategies, the high implementation costs also justify their current worldwide low applications.

"Incentive-based demand management strategies, as gaining increasing attentions because they are considered more acceptable by the public and policy makers." [4] Despite an abundance of abundant studies that have been conducted in the congestion pricing area, comparably few of those focused on incentives, their utilization in real-time demand management and travelers' reactions to them. Leblanc et al [11] "carried out a stated-preference survey in the San Francisco Bay Area to analyze how different incentive schemes can affect commuting decisions." [4] Along with the predictions performed by behavioral economics, travelers' sensitivity toward being charged was remarkably higher than being rewarded, but various sensitivities were raised towards different incentives, e.g. "cash rewards proved to be more efficient than an HOV pass. Such evaluations are fundamental in the design and optimization of real-time incentive schemes which may, on the other hand, benefit from personalization to account for such incentives." [4] An analogous study was conducted by Kumar et.al [12] in which a detailed behavior analysis and modeling were presented in favor of understanding the effects of incentives on traveler choices by using collected data from the Spitsmijden reward-based experiment. "The Spitsmijden experiment was a peak rewarding project in four highway corridors in the Netherlands to investigate the behavioral responses of personal vehicle users toward static incentives targeting departure time behavioral shifts. This peak rewarding experiment highlights the importance to design revenue-neutral incentive-based mechanism to ensure a sustainable outcome. Other experiments followed to explore the behavioral reaction to point-based, lottery-based, personalized or smartphone-based static incentives. All these proposed schemes are fundamental in capturing different behavioral shifts but are limited in effectively managing demand in real time." [4]

Optimization mechanisms targeting incentives have been studied and documented not long ago, e.g. Rey et al. [12] "evaluated a lottery-based revenue-neutral incentive mechanism to reduce congestion in urban transportation systems by promoting public transit usage during off-peak periods." [4] Through their investigation, a theoretical equilibrium was acquired for the proposed decision-making game which was validated through monetized laboratory experiments. Hu et al. [13] introduced a point-based routing guidance smart phone application which was working with real-time traffic information whereby alternatives assumed to mitigate the network traffic congestion, such as off-peak time interval trips, using less congested routes, were assigned higher points which were exchangeable for rewards. "A pilot study was deployed in Los Angeles, California, in 2013 and results showed shifts in travelers' behavior but overall network performance measures were not presented. Gao et al. [14] proposed RoadRunner, an in-vehicle app for quantity control with no roadside infrastructure cost. Harnessing vehicle-to-vehicle communications, the number of vehicles in a network is managed through a token-based exchange mechanism. Although the exchange and control formulation were not fully explored in this study, both software and hardware were successfully tested in field experiments and network performance assessment was carried out in simulated environment." [4]

Regarding the conducted research and investigations, it may be concluded that, theoretically making travelers decide to switch to alternatives results in network efficiency improvement, for instance off-peak trip making, less congested route choice or transit and shared ride usage, leads to outstanding savings in externalities. Although remaining challenging problems are design, implementation and incentive strategies operation, smartphone apps, which can be found easily in the app store for various environments, are gaining considerable attention in making travelers shift their travel behavior to more efficient alternatives. "Yet, real-time incentive schemes optimization that accounts for predicted network conditions are still rare, targeting a limited population segment and/or limited set of traveler's choice dimensions." [4]

1.3 Overview of Tripod:

Tripod aims at maximizing the system-wide energy efficiency of the multi-modal transportation system in a real-time scheme through encouraging travelers via personalized incentives to adopt alternatives with less energy consumption rates [15].

"When starting a trip, travelers can access Tripod's personalized menu via a smartphone app and are offered incentives in the form of *tokens* for a variety of energy-reducing travel options, in terms of route, mode, ride-sharing, departure time, driving style and actual trip making. Options are presented with information to help travelers understand the energy and emissions consequences of their choices. By accepting and executing a specific travel option, a traveler earns *tokens* that depend on the system-wide energy savings she or he creates, encouraging travelers to consider not only their own energy cost, but also the impact of their choice on the system. *Tokens* can then be redeemed for services and goods from participating vendors and transportation agencies [15]. "Tokens, Tripod incentives are provided through a personalized mobility menu via Tripod's smartphone Interface (UI) to the Tripod users. (see figure 1)." [3]

In order to achieve the system-wide energy efficiency, a real-time optimization on the number of tokens being offered in the menu will be performed, considering the limited incentive budget as the constraint. Maximizing the system-wide energy saving is a kind of complicated problem that requires taking the interaction between system-wide supply and demand, individual specific preference toward various alternatives, and token awarding into account. To deal with such a challenging case, [15] "decomposed the energy efficiency maximization into a bi-level structure with two loosely coupled problems: System Optimization (SO) and the User Experience (UE)" [3] (see Figure 2).

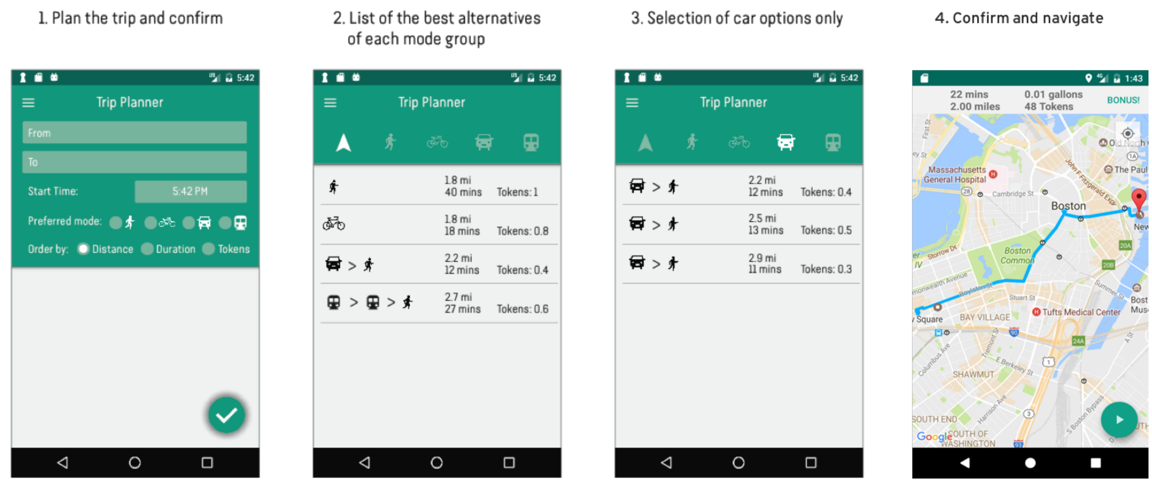

Figure 1: Tripod menu UI [15]

SO, the upper level, defines the overall optimization policy and UE conducts optimization at the lower level, for every individual user, and personalization, consequently. Token energy efficiency (TEE) by which these two challenging problems are being linked together, is the amount of energy a traveler must save to gain a token. TEE is the decision variable in SO optimization problems and is being used by the UE in any menu personalization, triggered by each trip request from a Tripod user's end (see Figure 2). SO not only provides UE with the TEE value, but it also prepares a full choice set of alternatives, "consistent with UE's policy predicted attributes" [3], to be considered in the menu personalization. SO, will be elaborated on more in the following by bringing its formulation, implementation, and performance into the light.

The User Experience (UE) is composed of three modules: User Optimization (UO), User Interface (UI), and a Preference Updater. Generating a personalized menu of travel options for each Tripod user per their request is the User Optimization module's course of action which takes advantage of the updated information and incentives based on the system-wide

TEE, the transportation performance predictions, and the energy impacts provided by the SO. To compute the associated tokens with the menu alternatives, UO primarily computes their corresponding energy saving, the amount of energy being saved in comparison to that of the predicted user choice (every individual's predicted choice with no tokens). Eventually, the number of tokens is obtained by dividing the energy saved by the current TEE value. "The UO then selects the alternatives that are attractive to the traveler based on a utility function, where coefficients for explanatory variables that represent personal tastes estimated from historical choices and values of alternative attributes such as travel time and energy cost are calculated based on the predicted information from Tripod's SO." [3] The generated menu is personal and represents the traveler's interest and not only retains the system architecture's sustainability but also stimulates the travelers to choose more energy-efficient options through providing users a precise energy cost and real-time information such as accident notifications. [16] expatiates on the UO formulation and preference updater.

To summarize, SO and UE, Tripod's separate optimization structures, conduct two dependent problems. The former "optimizes the entire transportation system at every roll period, say 5 minutes, whereas the latter optimizes in real-time an individual menu per each trip request besides keep tracking of Tripod users' preferences from their menu selection." [3] SO takes the updated users' preferences to improve its prediction strategies. [15] and [16] develop deeper discussion and insights regarding overall Tripod architecture and the UE optimization framework.

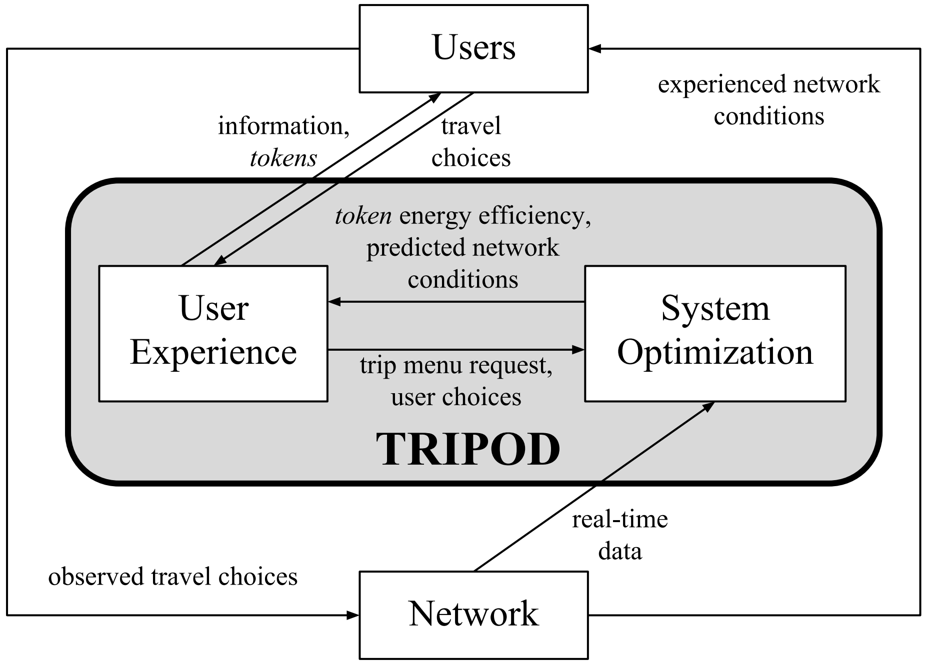

Figure 2: Tripod Architecture [15]

1.4 Tripod's Rationale:

To elaborate on the rationale behind Tripod's implementation and design, essential premises need to be introduced in more detail before discussing the architecture design, implementation and solution formulation.

1.4.1 Tripod and traveler's decision making

- A traveler is assumed to make mobility choices at the origin and en-route. A mobility choice is defined by various components: mode (drive alone, shared modes, bike, walk, etc.), departure time, route and driving style (in case of driving). These dimensions are incentivized through Tripod along with the trip cancellation option. However, trip cancellation requires remarkable modifications to the herein proposed approach in both behavioral and optimization implications which is out of this research's scope.

- While en-route, a traveler cannot change mode or departure time, but can change route and/or driving style;
- Only opt-in travelers (subset of the travelers population) can access the Tripod app and make a trip request;
- For each user, trip requests can happen both at the pre-trip and en-route level and form control points from whom high fidelity personal data is available through the Tripod app;
- At the Tripod system level, requests can be received at any point in time;
- Tripod incentives are provided in the form of *tokens* for each alternative in the personalized trip menu for a given requested trip;
- If a user decides to select one of the Tripod menu options, the Tripod app will track the users during the trip, and *tokens* are provided only if the realized trip coincides with the selected option;

1.4.2 Tripod Tokens and Rewards

- "Tokens are awarded to a menu option proportional to the system-wide energy saving, which encourages opt-in travelers to consider not only their own energy savings but also the impact of their choice on the system;
- *"Tokens are not allocated directly to specific users, but are awarded to any menu alternative selection and execution that contributes to the optimization of system-wide energy savings;*

- “The marginal energy saving for each alternative presented to the Tripod user is calculated based on predicted traffic conditions for the requested trip and user specific preferences;
- “The internalization of the marginal cost through *tokens* will potentially drive the system towards optimum;
- *“Tokens* can be redeemed for services and goods (rewards) at participating vendors and agencies. The available services and goods are assumed to be static and can be translated to a set on monetary values of reference for each reward;”
- “The actual *token* value can be perceived differently by each user;
- *“Tokens* can be accumulated; a user can either use enough tokens to purchase at least one reward or save and accumulate more *tokens*.” [5]

CHAPTER 2

SYSTEM OPTIMIZATION ARCHITECTURE

2.1 Overview

In order to get insight about System Optimization's operation, it should be noted that first and foremost, SO estimates the current state of the multi-modal transportation network followed by a prediction of the network state given various awarding strategies in terms of token allocation, i.e. different TEE values. Then, it estimates the energy savings based upon the network conditions per every token awarding strategy. Eventually, the UE will be provided with system–wide optimum TEE value as of energy savings per token.

To achieve this goal, the System Optimization builds two separated, although correlated, models called DynaMIT and TripEnergy. The former is a state-of-the-art, real-time simulation-based dynamic traffic assignment model that provides predictions of the multi-modal network performance aligned with the users' behavior to the provided information and incentives while the latter estimates the energy impacts of travelling. The next section will more deeply discuss DynaMIT extensions and how they are modeling the multi-modal aspect including transit, carpooling, walk and so forth besides incorporating the behavioral response to the provided information and incentives. Carpooling is defined as a private mode of travel which consists of two travelers in a single vehicle with the same origin, destination, and departure time interval (within the same roll period).

All the above-mentioned steps are carried out within every roll period of DynaMIT run which result in the optimized Token Energy Efficiency (TEE) value, represents the system-wide energy savings with regard to the predicted traffic conditions and that of the future prediction horizon. The optimized TEE is achievable through operating “a simulation-based optimization in real-time within Tripod” [3] containing three major simulator components as follow:

I. Supply Simulator
II. Demand Simulator
III. System Optimizer

The first and second simulators are dealing with the multi-modal simulation aspect of the SO optimization run in terms of simulating the responses to various TEE values while looking for the optimal TEE value based on the simulated system responses is under the System Optimizer’s jurisdiction. The Supply and Demand simulators are extended with new functions such as including presuming travel modes other than merely private car. In addition, “the demand simulator is extended with Simulated User Optimization (SUO), which simulates the user optimization of the UE, i.e. the generation of the menu of the alternatives shown by the Tripod app, including the tokens allocated to the alternatives” [3] by which the accuracy of users’ responses to the token awarding boosts. On the other hand, “the supply simulator is extended with energy estimation, which allows the computation of the energy consumption of the whole system, as well as that of each travel alternative.” [3] Figure 3 represents the SO architecture and the way of integrating the above-mentioned components for acquiring the optimal Token Energy Efficiency value.

In order to have a glance over the System Optimization module, it would be beneficial to explain the steps that are taken within each roll period and elaborate on every step in the following sections. At the beginning of a roll period, the current state of the network is required to be well-known which is done by performing a state estimation that takes the historical demand and supply parameters as initial values, takes the real-time occurrences (e.g. accidents) into consideration. Then, to raise the precision of the estimation, an online calibration versus the real-time measurements such as travel time, speed and traffic counts will be carried out. It is assumed the state estimation generates a roughly precise network state close to the current network condition, Origin-Destination (OD) of the trips, and the behavioral parameters of travelers by which their choices and responses to token awarding is simulated. In other words, within the state estimation, the previously mentioned extended simulators, Demand and Supply, are interacting to generate estimated traffic conditions. The simulated vehicle trajectories are sent to the energy estimation within the Supply Simulator to produce energy consumption estimates. On the other hand, in the Demand Simulator, SUO receives trip requests of the simulated Tripod users and generates personalized menus to simulate users' responses in addition to allocating tokens based on the generated TEE of the previous roll period.

Then, the optimization module uses the estimated network state as an input to run, and DynaMIT predicts traffic and energy conditions for the future prediction horizon through the demand and supply interaction with different TEE values. Eventually, the best token energy efficiency value will be selected by the System Optimizer for the next roll period.

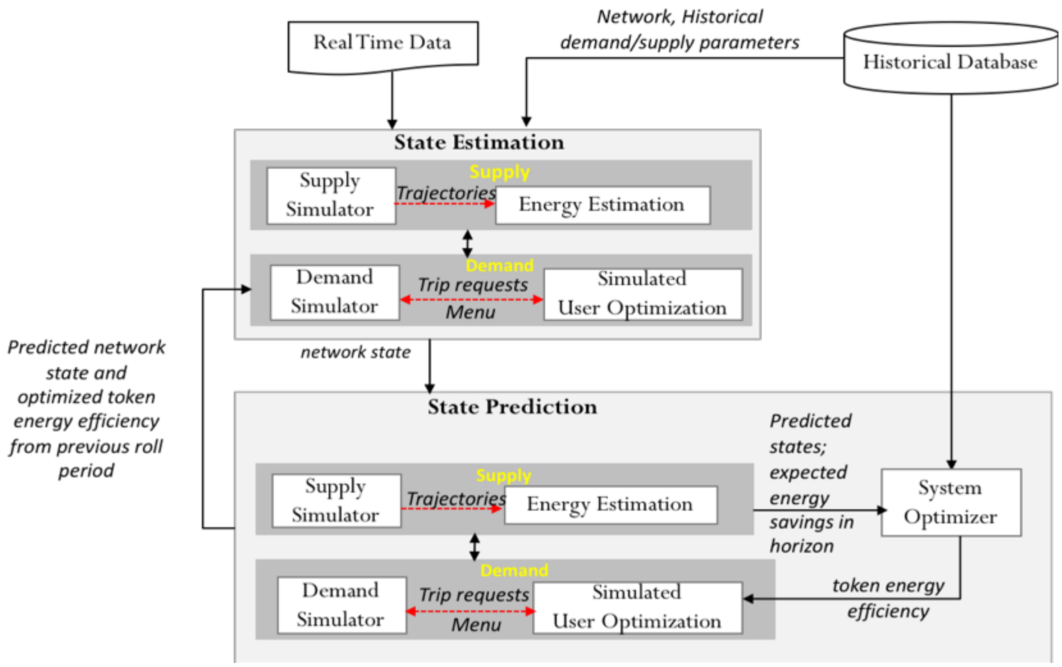

Figure 3: The System Optimization Architecture

2.2 Multi-modal transportation demand and supply models:

This section more deeply details the Demand and Supply Simulators of DynaMIT and how they are interacting within the state estimation and prediction modules.

2.2.1 Multi-Modal Demand Simulator:

The Multi-Modal Demand Simulator employs two different representations of demand, aggregate and disaggregate, in terms of travelers and passenger car equivalents, respectively. The disaggregate representation is utilized to model individual users' pre-trip and en-route decisions such as their responses to the provided information and token awarding. The aggregate one, "in the form of time-dependent Origin-Destination matrices, is also used to estimate and predict the multi-modal OD demand. The demand simulation process of DynaMIT system is captured by the five steps shown in the Figure 4 below. The aggregate historical flows are first disaggregated into a habitual list of drivers (Step - 1). These drivers then make various choices that could change departure *time* and route (Step 2). This update, disaggregate representation is aggregated back into OD matrices (Step 3) before the online calibration step (Step 4) is performed to estimate OD matrices. Finally, the adjusted matrices are disaggregated (Step 5) to generate the final list of drivers. An important feature of the original DynaMIT system is that there is a "one to one" correspondence between travelers (those make a trip) and vehicles on the network. In other words, each individual may be viewed as a driver of a vehicle. In order to model a multi-modal environment, maintaining both disaggregate representation of individual travelers and aggregate depiction of demand in terms of traveler and vehicle trips is of tremendous importance." [4]

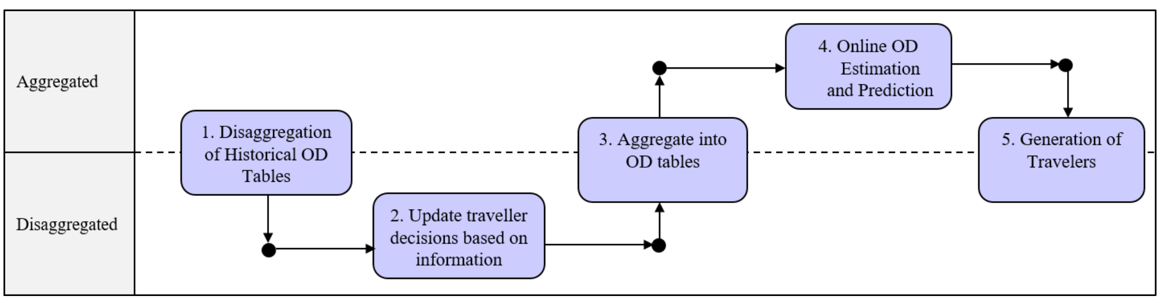

Figure 4: Multi-modal Demand Simulation steps

Figure 4 (above), 5 and 6 (below), depict the Demand Simulator diagram. The historical information consists of mode-wise time-dependent OD demand matrices specified in terms of traveler trips. The first step in the Demand Simulator is disaggregating the historical OD matrices to produce a population of travelers having been assigned a habitual route, mode and departure time. Then, a pre-trip behavioral update is performed whereby every traveler updates their choice of mode, route and departure time regarding the provided prevailing traffic conditions and tokens awarded (for Tripod Users). “The pre-trip choice is formulated as a nested logit model [17] whose structure is depicted in Figure 7. (DT stands for Departure Time interval). The specification of the choice model includes attributes such as Travel time, Travel Cost and Monetary value for tokens awarded, as well as the ASCs (alternative specific constant). For example, the utility of an arbitrary path *p* under the mode-change (to car) and path-change nest for a habitual transit traveler *n* with a habitual departure time interval *h* is given by:

$$U_{\mathrm{np}} = \beta_{n-TT} TT_{ph} + \beta_C \left(C_{ph} - \alpha_{np} \gamma TK_{nph} \right) + \varepsilon_{np} \tag{1}$$

where β_{n-TT} is the travel time coefficient generated based on a lognormal value-of-time distribution, β_C is the cost coefficient, TT_{ph} is the predicted (or historical, depending on whether the traveler has access to information) travel time on path *p* in time interval h, C_{ph} is the monetary cost, γ is the market value of the token, α_{np} is a unit-free *token* value inflation/deflation factor, TK_{nph} is the number of *Tokens* allocated to individual *n* for using path *p* in interval *h* and ε_{np} is a random error component that is *i.i.d.* Gumbel distributed.” [3]

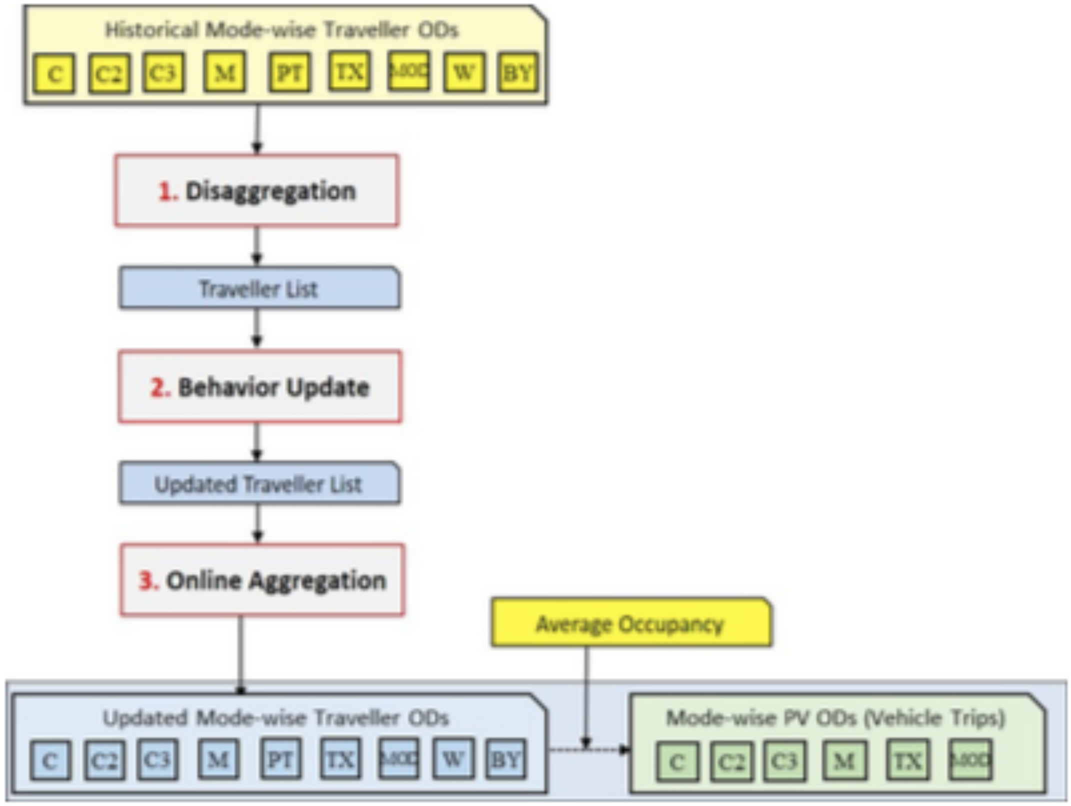

Figure 5: Multi-modal Demand Simulator – Steps 1 to 3

Updating the list of travelers is the second step, which is followed by step 3, where the list is aggregated back into mode-wise OD matrices in terms of traveler trips. However, in the case of the private vehicle mode, the mentioned ODs are converted to vehicle trips by using an average occupancy. In the OD estimation, in the fourth step, which is called online calibration, the most recent surveillance data from the network are utilized to adjust or estimate OD demands in order to minimize the difference between the simulated and observed traffic counts. The OD estimation module takes advantage of the supply simulator (see the next section) and the estimated private vehicle ODs, in terms of vehicle trips. Eventually, the above-mentioned matrices are then "used to compute estimates of mode-wise private vehicle ODs (vehicle trips) based on historical modal splits which, in combination with the historical transit ODs, yield the estimated mode-wise OD demands in traveler trips. These are used to generate the final traveler population for the current estimation interval." [4]

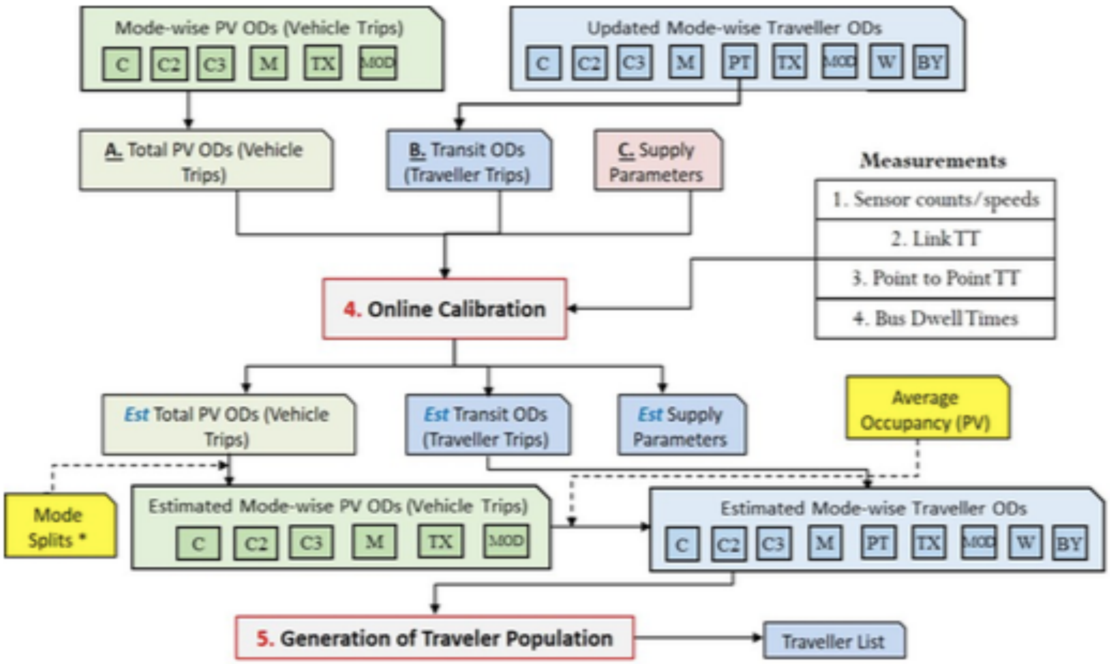

Figure 6: Multi-modal Demand Simulator – Steps 4 to 5

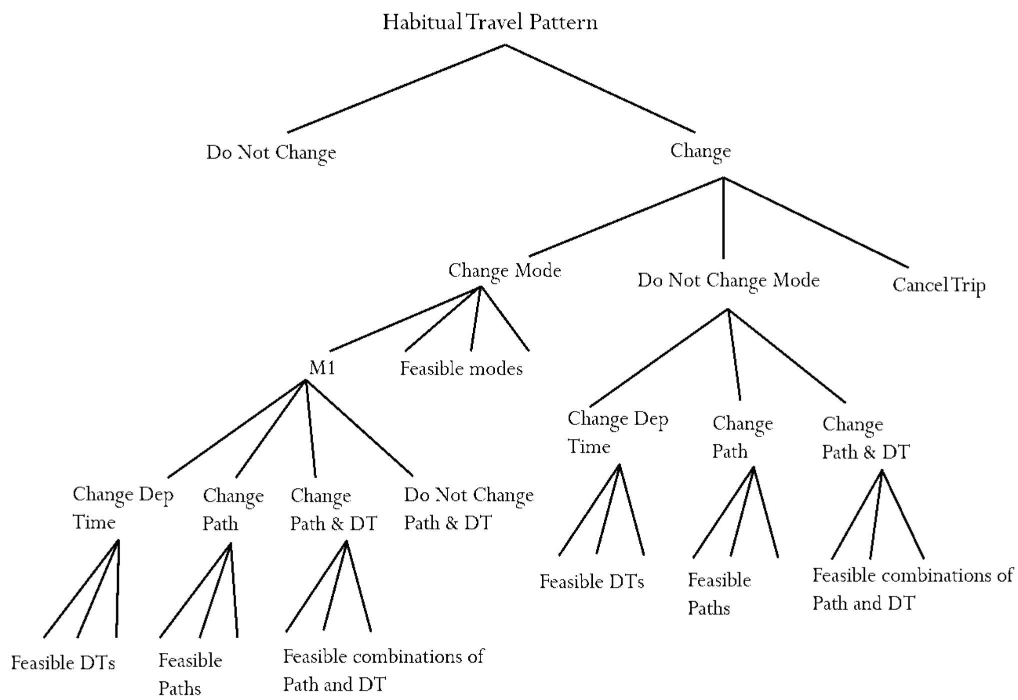

Figure 7: Structure of Pre-Trip Behavior Update Model

2.2.2 Simulated User Optimization (SUO)

In order to boost the accuracy of the estimation and prediction, a simulation within the demand simulator will be performed to find out what the options provided to the users will be. SUO runs the mentioned herein simulation, obtains all travel options available for a given set of origin, departure time and destination, token energy efficiency (TEE) of either the previous roll period or optimized trial value, and finally the Tripod users' characteristics and preference parameters. The following 3 steps, within the SUO, for generating a personalized menu of travel options with their corresponding awarded tokens are executed:

1. "For a specific user n, the number of tokens assigned to travel option i $(i = 1,\ldots,C_n)$ *is*

$$\max\left(0, \frac{E_{n0} - E_{ni}}{e}\right), \forall n, \forall i \in C_n \quad (2)$$

E_{ni} is the energy consumption of travel option *I* for user *n*, E_{n0} is the expected energy consumption of user *n* without tokens, $\sum_{i=1}^{C_n} E_{ni} P_{ni}$, where P_{ni} is the probability of user *n* chooses option *i* without tokens, and *e* is the TEE.

2. A personalized menu (a subset of travel alternatives out of all travel alternatives C_n) is generated based on choice probabilities of travel alternatives with tokens assigned in Step 1. SUO maximizes the expected choice probability across the *M* options on the menu by solving the following problem.

$$\max_{\sum_{i=1}^{N} x_{ni} \leq M, x_{ni} \in \{0,1\}} \sum_{i=1}^{C_n} P_{ni}^{*} x_{ni} \quad (3)$$

The binary decision variable x_{ni} denotes whether to include option *i* or not in the menu. P_{ni}^{*}*i* is the probability of user *n* chooses option *i* with tokens. The solution is to simply pick the top M options by sorting P_{ni}^{*}.

3. Remove tokens assigned to options not on the menu generated in Step 2." [3]

2.2.3 Multi-modal Supply Simulator

Evaluation of the performance of the network which includes formation and dissipation of queues, spillback effects and impacts of accidents and bottlenecks, is essentially required. This has been noted, the Supply Simulator of DynaMIT, despite it is mesoscopic [Sec 1.4.3 [18]] and simulates individual vehicle movement runs in a simplified manner, captures traffic dynamics and does the mentioned herein evaluation. The representation of the traffic dynamics is through the macroscopic speed-density relationships and queuing theory. The multimodal supply simulator derives largely from the original mesoscopic simulator [Ch.10 of [18]] with two key enhancements: 1) Traveler Movement: transit travelers' agents are introduced and 2) Buses: a *controller* has been developed to manage the fleet of buses. The traveler and Vehicle are two main components of a transit trip, the sequential stages of which are shown in Figure 8 below (PT stands for Public Transit).

The design of the supply enhancements to model buses involves two components: 1) Bus controller and 2) Vehicle movement module. The Bus controller operates the fleet of buses on the network (fleets of multiple operators are also practical) and obtains a list of bus lines with their related frequencies/headways and stops from the database.

In order to capture the dwelling of the buses at stops and their corresponding effect on the traffic stream, the existing vehicle movement models are adapted accordingly. "Since DynaMIT model spillback effects and congestion via its queuing part at the downstream of each segment, all segments containing a bus-stop are split at the location of the stop in order to capture the queuing caused by bus dwelling." [3]

The movement of buses consists of 2 parts: (i) Buses move between the stops and (ii) they move into and out of the stops. The former is identical to that of cars where the speed-density and queuing models control their movements. In terms of moving into and out of the bus stops, the buses run toward the stop while reaching the end of the segment with a bus stop if the residual capacity is positive. Otherwise, they start to form a queue and cause the vehicles behind to stop, and the formed queue does not start to dissipate as long as there is no residual capacity. On the other hand, turning back to the traffic after serving the bus stop relies on the acceptance capacity of the downstream segment. They can merge the traffic if there is no downstream queue; otherwise they have to wait at the station.

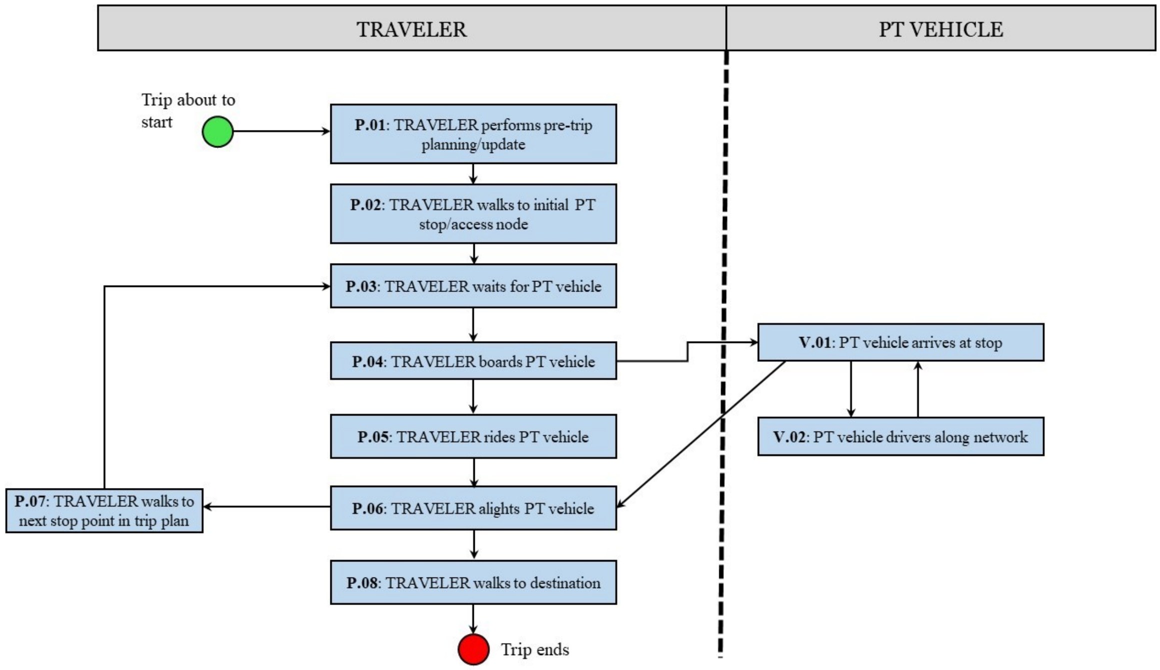

Figure 8: Traveler Movement: Stages of a Transit Trip

2.3 TripEnergy CA

Trip energy aims at providing energy estimates to the System Optimizer and SUO, whereby they will be used in the system's overall objective function and calculate the number of tokens per menu, respectively. In the latter, since the energy savings are also provided as information on trip attributes employed in calculating the number of tokens per menu alternative provided to Tripod users, affect travelers' decision making. Per the System Optimizer, the overall energy consumption is used as part of the objective function in each rolling horizon pursuing the optimal TEE value. The optimal TEE value is passed to the SUO in order to allocate tokens for options per each individual user's choice set to maximize the expected choice probability across the menu options and simulates the user's menu choices. "These two TripEnergy outputs will both be produced through combining inputs from DynaMIT's State Prediction (SP) module with high-resolution data on driving behavior collected from GPS surveys." [4]

CHAPTER 3

OPTIMIZATION FORMULATION

3.1 System Optimizer

"This section provides a high-level formulation of the SO problem, based on [15], which will be solved through the heuristic method in the following section.

The predictions of network state are performed in discrete time steps with a time interval of Δ, called *roll period*. During time interval $[t - \Delta, t]$, we perform the computation to predict what will be the network state in the *prediction horizon* $[t, t + H\,\Delta]$, where $H \in \mathrm{N}$.

The vector of starting times for the roll periods contained in the prediction horizon for time t is here denoted by $\tau = (t, t + \Delta, t + 2\Delta, \ldots, t + H\Delta)$. Alternatively, the notation τ is also used to refer to the prediction horizon $[t, t + H\,\Delta]$, with the specific use evident from the context. The decision variable for SO is TEE, which represents the amount of network-wide energy savings that must be realized by a user in order to be awarded one token. The TEE is considered to be constant within each roll period. The token efficiency values related to a prediction horizon are represented by the vector $e\,(\tau) = (e\,(t), e\,(t + \Delta), \ldots, e(t + H\,\Delta))$. The total energy savings predicted within the horizon is denoted by $ES\,(e\,(\tau))$." [3]

3.1.1 DynaMIT State Estimation (SE):

Regarding the description above, the SO performs an estimation of the network state by executing a cycle at any time t by taking advantage of the real-time data collected within the previous roll period $[t - \Delta, t]$, in addition to the real-time historical data from the database for that given time t. Having the estimation done, to minimize the discrepancy between the simulated measurements and their real-time values, calibration is essential.

The Tripod users' choices, given their individual menu and behavioral parameters such as sensitivity to tokens, are also taken into account within the DynaMIT State Estimation.

3.1.2DynaMIT State Prediction (SP):

At this stage, the SO loop is initiated, after the SE is completed, through running a state prediction. In order to do so, the supply-demand parameters, previous network condition and e (τ) are sent to the SP to predict how the network performance will evolve during the presumed prediction horizon τ which yields the predicted network state x (τ). The generated network state includes v^n (τ), users' entire trajectories or at least parts of their trajectories lie within the prediction horizon.

3.1.3 Energy Estimation:

Given the v^n (τ), e (τ) and x (τ) which stand for predicted user trajectories, token efficiency and predicted network states, respectively, TripEnergy [19] calculates the total energy savings *ES (e* (τ)) for the entire network within the prediction horizon. This is executed by comparing the predicted energy consumption with that of a baseline which is the SP simulation with no tokens, as below:

$$ES(e(\tau)) \;=\; \sum_{n=1}^{N} f(\upsilon_e^n, \theta^n) - \sum_{n=1}^{N} f(\upsilon_0^n, \theta^n) \tag{4}$$

where $\upsilon_e^n, \upsilon_0^n$ stand for the user trajectories resulted from providing tokens with respect to the e (τ) and without tokens, respectively. N is the number of travelers, θ^n are the travel mode parameters "(e.g. car design parameters, bus type, driving style etc.)" [3] and *f ()* is the energy consumption function per user trajectory.

3.2 Strategy Optimization Loop:

The primary objective of the Strategy Optimization is determining the optimal Token energy efficiency (TEE) for the *H* roll periods within the entire prediction horizon. For any given TEE value, the Simulated User Optimization (SUO) specifies the menu of trip alternatives with their corresponding assigned tokens offered to Tripod users; SP updates the demand and produces the new network states; the TripEnergy module finds the energy saving relative to the base-case which involves no tokens. With respect to the above-mentioned inputs and modules, the objective function of maximizing network-wide energy savings, the potential energy savings of the entire day is evaluated. This is an optimization problem with a constraint which is the balance of tokens at the end of the prediction horizon, $W(\tau, e(\tau))$, stand out. This noted balance is defined as the balance of tokens at the beginning of the prediction horizon minus token consumption during the prediction horizon for a given vector of $e(\tau)$ of TEEs and must be non-negative. The optimization problem is stated as below:

$$\max_{e(\tau)} ES\big(e(\tau)\big) \tag{5}$$

subject to: $$e(\tau) \geq 0, W\big(\tau, e(\tau)\big) \geq 0.$$

"The above optimization problem can be solved under two different scenarios:

1. The token energy value does not vary across different time intervals in the prediction horizon

2. The token energy value varies across different time intervals in the prediction horizon.

The first scenario, which is assumed in the current study, results in a single decision variable, and therefore a simple exhaustive search is used as the solution algorithm. The continuous interval (decision space) is discretized using a reasonable step-size obtained from trial- and-error. The objective function value for different TEEs can be evaluated in parallel and the optimal solution obtained in a single iteration of the optimization.

In this second scenario, however, exhaustive search is not a feasible option, as the number of function evaluations grow exponentially with the number of intervals in the prediction horizon. Therefore, it becomes necessary to use a more efficient optimization algorithm. Also, it needs to be noted that the objective function does not have a closed- form, therefore to evaluate a single set of TEEs we need to run a simulation (DynaMIT Prediction), which can be computationally expensive particularly for large networks such as the Greater Boston Area. Therefore, we use a Genetic Algorithm (GA) for scenario two. The main reason behind using GA is that it is easy to parallelize, i.e. multiple function evaluations can be computed in parallel during a single optimization iteration. GA starts by initializing a random set of TEEs from the search space. These are evaluated in parallel, a new set of TEEs is generated using the genetic operators of crossover and mutation. This new set is again evaluated in parallel. From the combined new set and the previous set of size 2*N*, the best *N* TEEs are chosen. From these best *N* TEEs, again a new set of *N* TEEs is generated and the process continues. **Figure 9** shows the algorithm diagram for a general control strategy." [4]

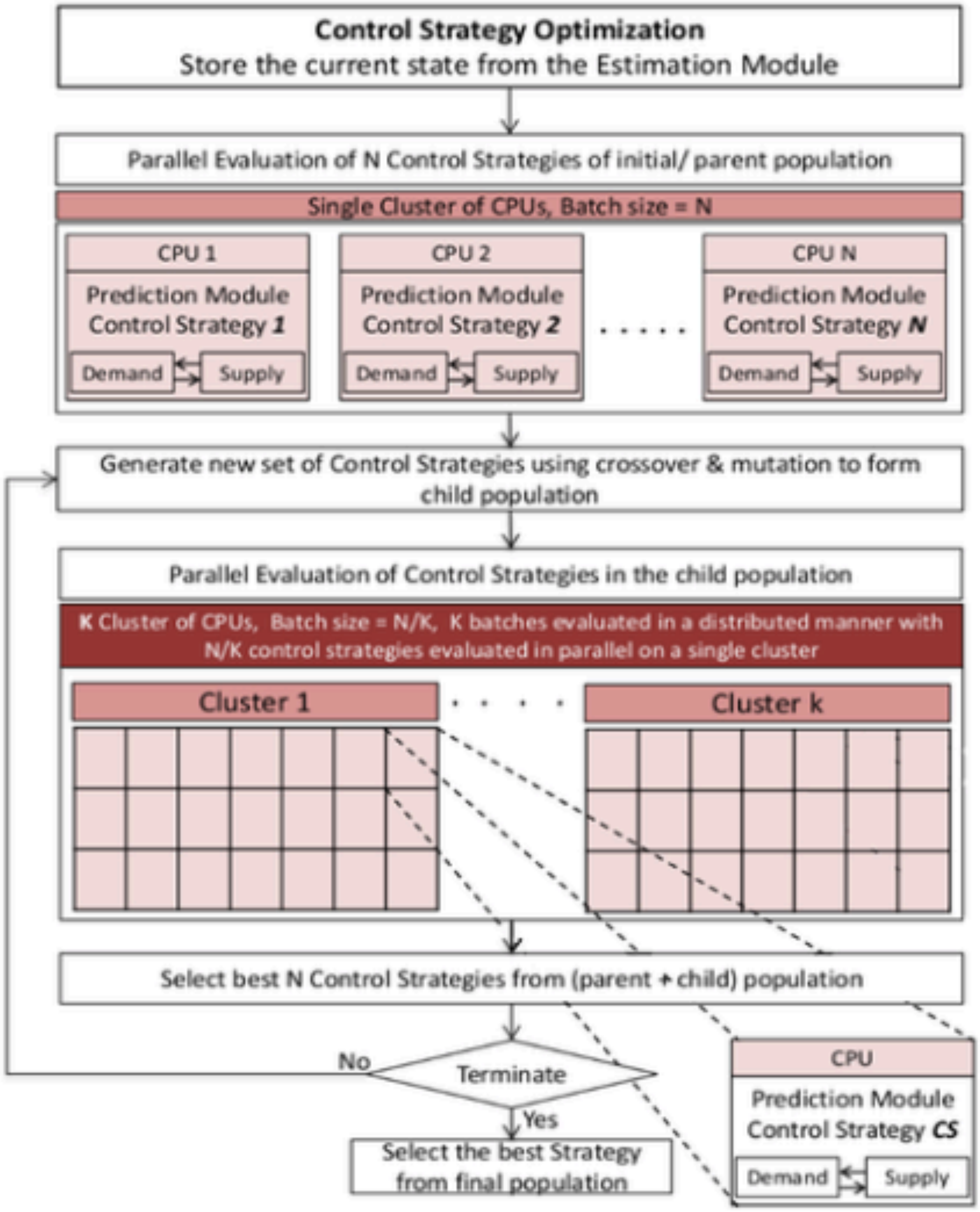

Figure 9: Genetic Algorithm for a Generic Control Strategy Optimization based on Combined Distributed and Shared Memory Computing Architecture

3.3 Data Generation

As discussed so far, within every roll period, DynaMIT State Estimation (SE) generates the current network state, OD matrix, the applied TEE and the number of tokens used which will be used for calculating energy consumption and savings within the corresponding roll period via the TripEnergy module. By the end of the day, all produced data are stored inside the historical database and are then sorted and organized for the beyond-horizon energy estimator purposes.

"The computation time and the memory used by Tripod depend on the (a) number of nodes in the network and in particular number of Origin-Destination pairs, (b) number of links and (c) number of travelers. We thus expect that the performance Tripod will achieve in the Greater Boston Area (GBA) will be observed in other metropolitan areas with the same characteristics. The original design of DynaMIT is able to perform estimation and guidance in small traffic networks such as Boston's Central Business District (CBD) but is not able to run in larger areas like GBA, due to excessive (i) memory consumption (more than 128GB) and (ii) execution time (more than 5 minutes running time to run a 5-minutes supply simulation with just 1000 cars on 1 origin-destination pair). The following section is elaboration on the proposed approaches to tackle discussed two problems as well as an approach, which called "network simplification", aims at giving a reduced representation of GBA." [4]

3.4 Network simplification for the GBA

As discussed above, in order to deal with associated complications in running a larger network, a simplified representation of the network is desirable. In order to obtain a new simplified network (SN), the primary approach is removing the “less important” links and keep the “important” ones from the original network (ON). Particularly, keeping those in the higher category rating such as freeways and expressways is of high importance, then retaining those most used links, based upon the traffic counts is the next concern. Consequently, some of the origins and destinations of the trips of the ON may no longer be present in the SN, thus to tackle with the missing nodes, their corresponding origins and destinations are designated to the closest nodes in the simplified generated network. Moreover, some of trips, such as “internal trips” whose origin and destination are both in the identical Traffic Analysis Zone (TAZ), shall be eliminated in order to keep the compatibility between size of the simplified network and overall number of trips. Eventually, in case of not having met the compatibility criteria between the size of SN and total trips, shortest trips may be removed to be the point at which the target number of trips, with respect to the corresponding reduced network size, is reached. Noted that, “the effects of the accuracy of the control after this simplification process have yet to be verified.” [4]

“In this study, two simplified networks are used in particular, Network A with 27870 links (around 60% of GBA network) and Network B with 6807 links (around 15% of GBA network).” [4]

3.5 Parallelization

In order to simplify the process of partitioning and merging between processors and to eliminate race conditions pertaining to the proposed method, a parallel version of DynaMIT based off of geographic partitioning is implemented. The rationale behind this idea is "that staggering execution of neighboring partitions will avoid the problems that arise from their interaction. This parallelization is supposed to fully avoid race conditions.

In DynaMIT, some nodes depend on the execution of their neighbors at the previous time step while some depend on the state of their neighbors at the current time step. These dependencies are created by the order in which vehicles are advanced at each node. DynaMIT updates nodes always in the same order at each time step. At each node, vehicles at the node's uplinks are advanced in ascending order based on their distance to the node. A 'state' at a certain node here refers to a set of vehicles in its uplink s and their positions. Therefore, if node i and j are adjacent and at every time frame vehicle s at node i are advanced before those at node j, then the state at node j at time t will depend on that of node i at the time t; However, when advancing vehicles at node i at time t, those at node j will not have been advanced yet. This means that the state at node i at time t is actually dependent on the condition of j at the previous time step $t-1$ which will be denoted as $i < j$ from now on. Note that j will always advance its packets after i does. The implemented parallelization scheme ensures this ordering holds across processors.

Suppose the position of each node is characterized by (x,y) coordinates. The simplest partition can be assumed divides nodes in bands, based on their x coordinate. Then, a consistent ordering of nodes will be imposed, e.g. given two processors, M and N, without loss of generality, nodes are ordered such that those in *M* will update before any nodes in

N, denoted as M<N at every time step. While moving dependencies to the band level in this way simplifies the problem of avoiding conflicts, it does not eliminate race conditions at boundaries when executing all processors in parallel. To tackle this, we take advantage of the idea that traffic effects do not propagate instantaneously. In other words, the movement of a car driving in Harvard square, Cambridge, will not affect the movement of a driver in Kendell Square within the same time frame. Indeed, in the real world, these effects are constrained by speed limit and other physical restrictions on the network. In a simulation, they are similarly dictated by the maximum distance the system attempts to move a vehicle within a time step. This separation implies that it ought to be possible to eliminate some dependencies in the network such that certain bands can be executed in parallel without race conditions.

Indeed, bands are specified with colors such that adjacent bands do not have the same color. Moreover, the bands are designed long enough so that no vehicle can cross them within a single time step. At each time interval, all band of the fist color are executed in parallel which is followed by the second color and so on. The implemented design structure guarantees each vehicle can only either stay within the same band or go to an adjacent one, respectively with different color. In both cases, there are no race conditions, since not only nodes within a single band are updated serially by merely a processor, but also a single color is executed at a time. The described approach so far, one-dimensional bands where partitioning is only based on the nodes' x coordinates, can be extended to "region" as a two-dimensional space. **Figure 10** below, depicts the partition and coloring in both one and two-dimensional cases. The speed up achieved in the operations to advance vehicles using 2 and 4 processors in Boston CBD network are 21% and 40%, respectively.

Note that this parallelization approach leverages the physical limitations that constrain the range of vehicle movement within a time-step. On the contrary, information is not constrained to this limitation, i.e., an incident can influence the movement of vehicle in a remote part of the network if instantaneous information about it is sent to the travelers herein. Thus, to make the strategy work efficiently even in presence of information exchange, it is assumed that any information has a latency of at least a time step. Given that the time step used is small (in the range of 5 to 10 seconds), which is believed to be realistic and reasonable." [4]

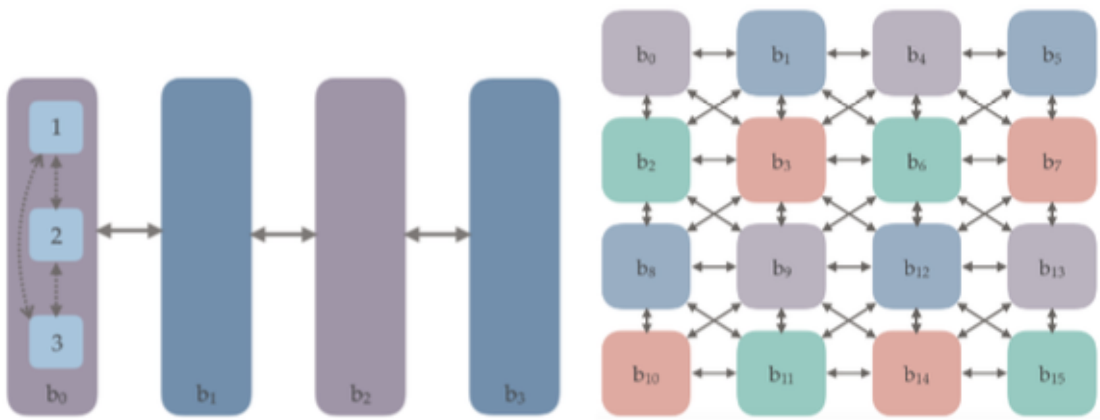

Figure 10: Schematic Representation of Partition and Coloring in One-Dimensional and Two-Dimensional cases to parallelize the Supply Simulator of DynaMIT

3.6 Online Optimization

In order to minimize the system-wide energy consumption of the entire transportation network, SO aims to find the sequence $\mathrm{e}(\tau)$ of TEE values for the next prediction horizon considering the token budget constraint. The Optimization will be performed on-line by adapting to the evolution of the network state. Consequently, $\mathrm{e}(\tau)$ is being updated over time and new values are appended each time the SO is launched. When the SO is launched, *M* instances of DynaMIT are run in parallel and all are controlled by a *Coordinator* which plays the following roles:

1. "Synchronizes the instances and ensures they work in real-time
2. Orchestrate their operations
3. Passes the essential information they require
4. Decides what will be the next TEE, $\mathrm{e}(t + \Delta)$ at each roll period *t*." [3]

SO passes the obtained $\mathrm{e}(t + \Delta)$ to the User Optimization module to be exploited for computing the number of tokens proposed to the users during the interval $[t + \Delta, t + 2\Delta]$. This comes from the requirement of real-time optimization where the $\mathrm{e}(t + \Delta)$ must be computed before its corresponding time interval $t + \Delta$.

The primary assumption is granting tokens to travelers on a First-Come-First-Serve basis where travelers who arrive sooner may be awarded despite having less energy saving. Considering the limited token budget, a contrivance should be proposed to prevent awarding such travelers. To do so, a constraint is taken into account by assigning a maximum per-period token budget. Referring to equation (2), when the TEE is "too small", a huge number of tokens will be awarded to the above-mentioned travelers with small energy saving. Due to the limited token budget, those who guarantee high energy savings but arrive later in the roll period will not be rewarded while they are supposed to be incentivized with higher number of tokens. On the other hand, in case the TEE being too high, a small number of tokens will be rewarded to travelers which in turn cannot incentivize them and affect their behavior. Therefore, detecting the optimal TEE value is not trivial and requires a more complicated approach. SO does so through heuristically exploring the impact of a set of TEE values within a given time interval.

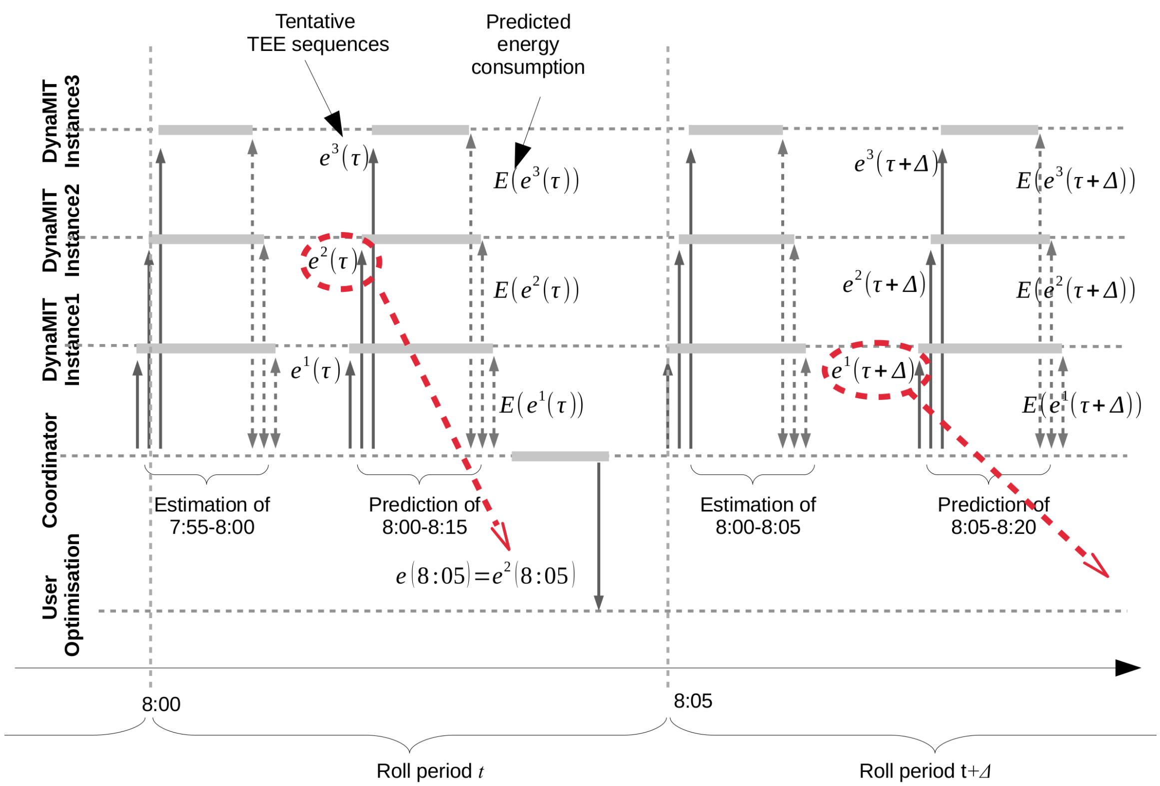

Figure 11: The on-line optimization procedure

Each of the DynaMIT instances, at each roll period *t*, runs a state estimation (SE) and state prediction, respectively. Whole instances should result in an identical state during the estimation phase; however, the Coordinator is in charge of checking this matter, since they are fed with the same real-time and historical data while may differ during the prediction phase because of using different $\mathrm{e}(t)$ values. To put it in another word, the Coordinator instructs each instance, at roll period *t*, to predict the network state within the prediction horizon. Each of the M instances predicts the effect of a different *future candidate TEE value*, denoted as $e^m(t)$ and m = 1, 2, …, M and is assumed to be applied in the entire prediction horizon τ, on the network state. TripEnergy is fed with the generated outputs, and eventually, each instance returns the predicted energy consumption $E^m(t)$. At this stage, the Coordinator chooses the instance m^* with the highest predicted energy saving and the least energy consumption alternatively as:

$$m^* = \underset{m}{\operatorname{argmin}}\, E^m(t) \tag{6}$$

The associated TEE value of the m^* instance, $e^{m^*}(t)$, will be utilized as the TEE value of the next roll period; $\mathrm{e}(t+\Delta) = e^{m^*}(t)$.

"The operations for the computation of the sequence *e*(τ) are depicted in **Figure 11**. Suppose a roll period of duration Δ = 5 minutes and prediction interval 15 minutes, i.e., *H* = 3. In order to describe the system when it is at time *t* = 8:00, which is the start of the roll period [8:00, 8:05]. Before the end of this period, SO must be able to provide the values of *e* (*t* + Δ), i.e., the TEE of the roll period [8:10,8:15]. To do so, the following sequence of operations takes place at 8:00:

1. The Coordinator triggers all the DynaMIT instances to execute their estimation phases, based on sensor data related to the previous 5 minutes, i.e., [7:55,8:00] and *e* (*t* − Δ). The goal of executing these estimation phases is to make the internal simulation model

consistent with real data. As discussed previously, all the instances have the same internal state in this phase. Observe that the parallel execution of the estimation phases of the instances corresponds to step 1 in Section "System Optimization Architecture".

2. The Coordinator assigns to each instance m a *candidate* TEE $e^{m}(t)$.
3. Each instance predicts the evolution of the network in the interval [8:05,8:20] and returns the predicted energy consumption $E^{m}(t)$.
4. The Coordinator chooses $(t+\Delta) = e^{m^*}(t)$, where $m^* = \mathrm{argmin}_m E^m(t)$ and communicates this value to the User Optimization module, which will use this value to determine the incentives that will be shown in the menus generated during the next roll period [8:05,8:10].
5. At 8:05, we start these operations again, with estimation based on real data related to [8:00,8:05]." [3]

CHAPTER 4

RESULTS

4.1 Effects of Control in Boston CBD

At this point, two types of effects of control are presented which stand out: “Open-loop” and “close-loop”. The former results are obtained from the SO while there is no interaction with the System Model module through which no online calibration for the Supply and Demand simulators with respect to real-time sensing information is being carried out. Consequently, “individual responses to incentives and the emerging system level performance measures are obtained from the SO simulator. The main purpose of executing the open-loop type tests is ensuring about the efficient performance of the SO assuming that state estimation and prediction are both performed correctly.” [4]

The close-loop type scenarios are being performed by implementing the controls generated by the SO and UE in the SM in an interactive manner. The following consecutive interactions between the different parts of Tripod, UE, SO and SM, occur during every roll period.

1. SM passes the sensing information of the most recent roll period such as traffic counts to the SO. Then, the SO conducts online calibration of its “supply and demand simulators following by running the system optimization loop with respect to state prediction for the duration of the rolling horizon to find the optimal TEE for the current roll period. Then, the predictive traffic and energy information and the obtained TEE value are transferred to the UE.

2. UE receives Tripod requests from simulated users in the SM, and generates personalized menu with tokens potentially assigned to each request given the latest TEE and predictive information from SO.
3. SM simulates each user's responses to the personalized menu as well as all other travelers' choices and load all travelers to the network. Sensing information is generated and provided to SO in batches (every roll period, usually 5 minutes)." [4]

The close-loop reflects the way Tripod would work in the real-world where SM is the real-world representative.

Noting that, the "beyond-horizon energy estimation module, where token budget allocation for the remainder of the day is endogenous to SO, is replaced by a roll period-based, exogenous token budget across whole the tests and results." [4]

In this section, the impacts of Tripod Optimization on the multimodal transportation system are evaluated in terms of energy consumption, travel time and mode share. In order to facilitate the analysis, a static scenario is assumed in which the TEE value will be fixed to a static number for entire simulation time interval and the penetration rate, the portion of travelers who are Tripod users and exposed to the information and tokens, is varying. Then, the penetration rate will be fixed, and on-line optimization over the static set up is performed, and its benefits are studied.

4.2 Simulation Scenario:

The experiments are conducted on the Boston Central District (CBD) network with 843 nodes, 1879 links, 3075 segments, and 5034 lanes, including both highways and arterials between 6 AM and 9 AM. Note that focus is restricted to the peak hours when the transportation system energy consumption is maximum. As expected, the energy gains would be lower in other time intervals, which we do not show for lack of space. The total number of travelers is 47588. The parameter values in the utility function (1) below are postulated as follows: $\beta^T = -0.01$, based on empirical studies in the literature, the value of time (VOT) is assumed to be log-normal distributed with a mean of \$18 per hour and standard deviation of \$5 per hour, the cost parameter β_n^C of an individual *n* is calculated based on a sampled VOT from the log-normal distribution. The monetary value of a token is γ = \$0.50. Tokens instead of dollars are used, as the full design of Tripod includes a marketplace where tokens can be exchanged and their monetary value determined by the market. In the current implementation, the marketplace is not in place, and thus a fixed value is assumed. The perception parameter $\alpha_n = 1$ for each individual *n*. As for the parameters of SO, we use a roll period length of $\Delta = 5$ minutes and a token budget constraint of 20K per roll period.

$$V_{ni} = \beta^T T_{\mathrm{ni}} + \beta_n^C (C_{\mathrm{ni}} - \alpha_n \gamma K_{\mathrm{ni}}) + \cdots \qquad (7)\ [3]$$

"The effectiveness of Tripod is evaluated by performing two simulations, at one of which tokens are awarded based on optimal TEEs computed by the system optimization (SO) module in a rolling horizon fashion and a base case, while the other one is involving DynaMIT with no tokens. In both simulations, all travelers receive real-time prediction provided by Tripod, and thus the difference in performance is due to tokens. The performance measures are the average travel time and energy consumption per vehicle and the distribution of travel time and energy consumption." [4]

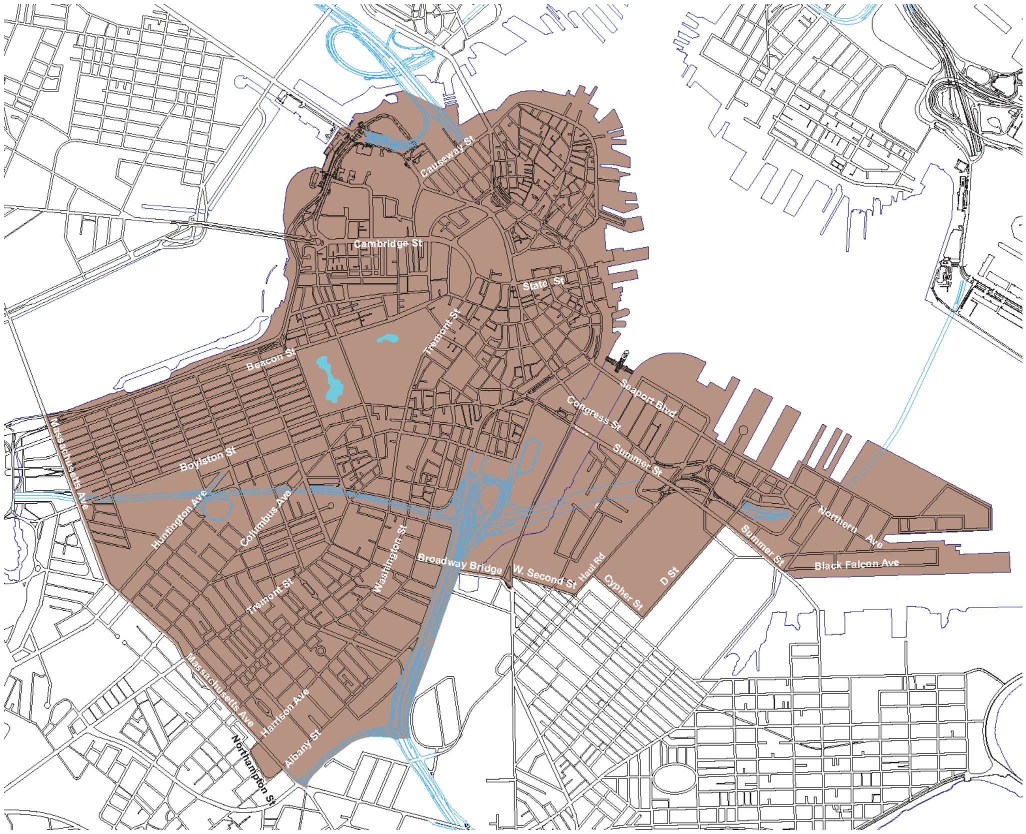

Figure 12: Map of Boston Central Business District (CBD)
(courtesy of Central Transportation Planning Staff)

4.3 Open-loop results with route/departure time choice in CBD

4.3.1 Single Mode results

Table 1: Open-loop Single Mode results with Route and Departure Time choice in CBD

Penetration Rate	Average Energy Consumption Per Trip (MJ)	Energy Saving Per Trip	Total Token Consumptio n (# of tokens)	Perceived Total Monetary Value of Tokens ($)	Average Travel Time (second)	Travel Time Saving Per Trip
0 (base case)	13.7	N/A	0	0	317	N/A
25%	13.1	4.6%	3633	1816.5	293	7.5%
50%	13.0	4.9%	10588	5279	289	8.8%
75%	12.7	6.9%	23167	11584	277	12.5%
100%	12.6	7.8%	31532	15766	275	13.0%

The preliminary tests were constrained by a token budget of 2000 tokens per 5 minutes (a total of 72000 over 3-hours running time). Due to models not having been calibrated, the absolute values of the presented results are not used to justify the effectiveness of Tripod. Instead, the discussion will be elaborated on the relative magnitudes and general trends between the results.

As illustrated in **Table 1** above, various results such as average energy consumption, average travel time, etc. are depicted as a function of Penetration Rate (PR). Noting that, the base case is defined as the scenario in which there is no Tripod user involved and consequently no token is consumed and presented via 0% penetration rate. Per the presented results, energy consumption decreases as the PR increases, as expected, since more travelers use Tripod, which in turn guarantees energy savings through offering more energy-saving alternatives. However, the rate of decrease is not monotonic as a function of the penetration rate, and this suggests a highly non-linear underlying system, and specifically, the effect of saturation with respect to the ascending trend in the PR. On the other hand, token consumption is a monotonic function of the penetration rate since saturation effect has nothing to do with this matter, and the more travelers use Tripod, the more tokens will be consumed.

However, it should be noted that the optimal time-dependent TEEs (inversely proportional to the number of tokens assigned per unit of saved energy) for different penetration rates are potentially different. The average travel time savings accompanies energy savings, and the CDFs at a 100% penetration rate in **Figure 13** show that savings are across the board, instead of focused on part of the travelers at the expenses of others.

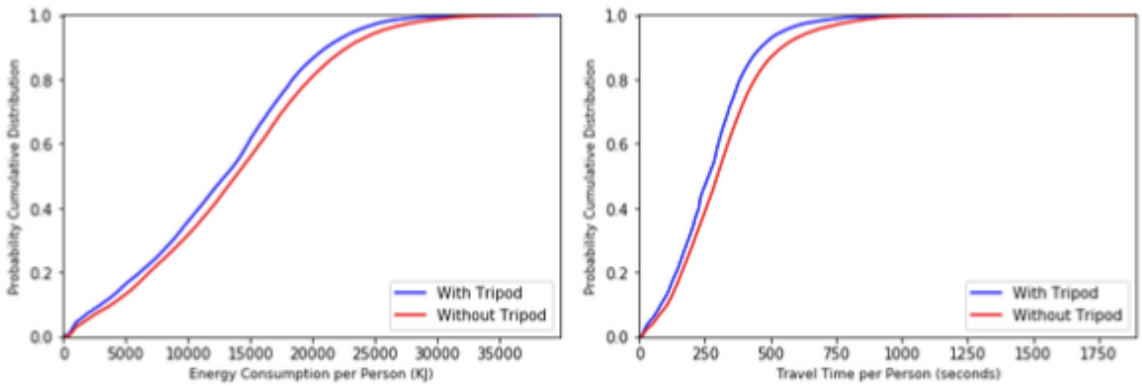

Figure 13: Energy and Travel Time CDFs with and without Tripod (at PR=100%)

4.3.2 Impact on the multimodal transportation:

In this section, the observed impacts of the online Tripod Optimization on mode share, average personal energy consumption, average personal travel time and token consumption with respect to different penetration rates are presented. "Note that the energy saving of Tripod depends on a myriad of factors, including but not limited to the penetration rate PR (the percent of travelers use Tripod), the sensitivity of travelers to incentives, the spatial-temporal distribution of the demand and the availability of attractive transit options. The penetration rate is a major factor that is directly related to the investment in the app deployment and thus the focus of the following computational tests. In contrast, other factors are less controllable, e.g., the spatial-temporal distribution of demand and the sensitivity of travelers to incentives mainly depend on the broader economic, social and demographic developments and the availability of attractive transit options requires significant capital investment besides the app. Note that, for the sake of simplicity, we do not model the possibility for a Tripod user to opt out. However, if a user does not find the proposition from Tripod attractive, he/she will simply ignore them, thus not contributing to the energy savings we will show later." [3]

Table 2: Open-loop Multi-Modal Results with Route and Departure Time choice in CBD

Penetration Rate	Average Energy Consumption Per Trip (MJ)	Average Energy Saving Per Trip (MJ)	Average Travel Time (second)	Travel Time Saving Per Trip	Token Consumption per 5-min (# of tokens)
0 (base case)	7.8	N/A	282	N/A	0
25 %	7.3	6.4%	269	4.6%	873
50%	6.7	14.1%	272	3.5%	1823
75%	6.4	18.0%	287	0.0%	2172
100%	6.2	20.5%	314	-11%	2357

The effects of Tripod optimization on the mode share are represented in **Figure 14** with respect to the penetration rate. Intuitively, the more travelers use Tripod, the higher PR, the more the share of greener modes will be. In another word, while more travelers use Tripod, greener modes such as bike, walk and carpooling will attract more users compared to the drive alone mode due to their higher energy savings. Consequently, their mode share would be significantly higher than that of the Drive Alone mode. In addition, since the carpool mode is potentially more efficient than the bus, walking and/or biking in terms of travel time as no pick-up or drop-off time is involved, its share is remarkably higher than those of green modes.

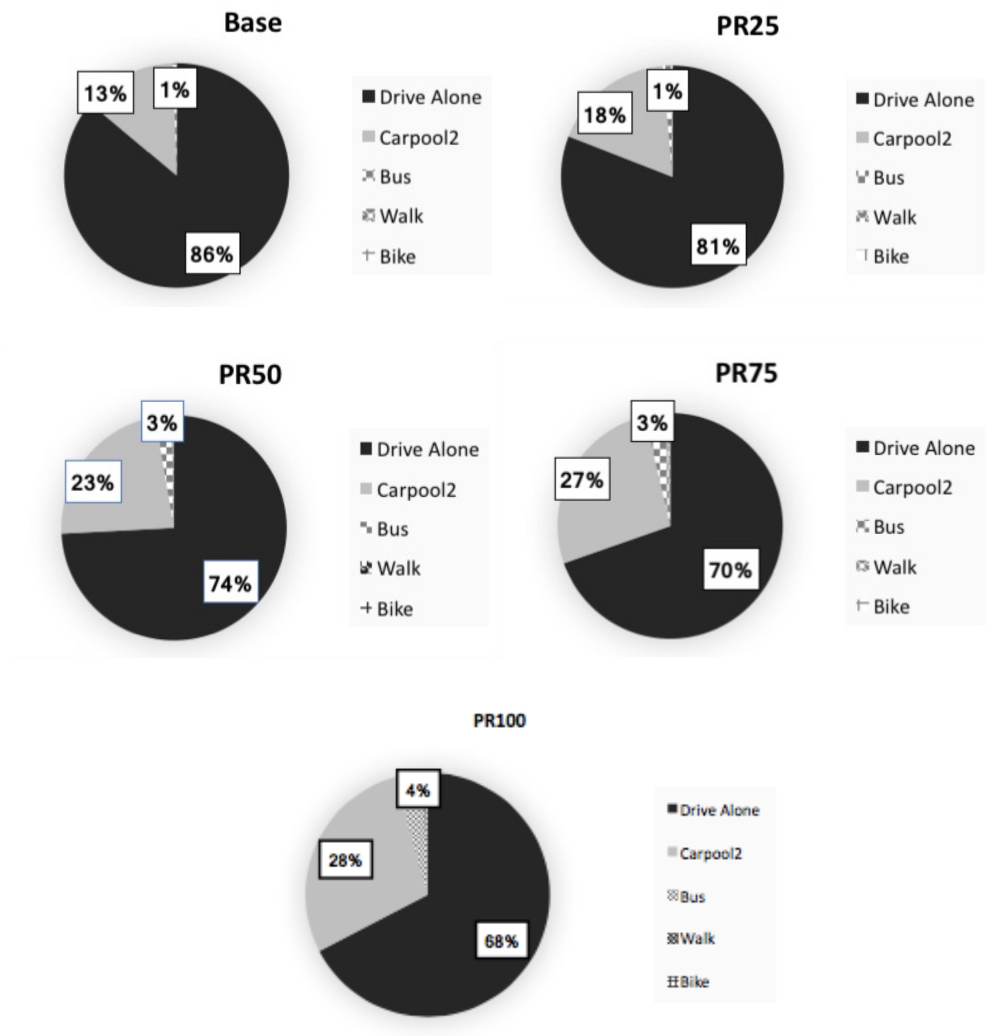

Figure 14: Mode share with various Penetration Rates (PR %)

The changes of the average energy consumption per trip in mega joule (MJ) with respect to changes in the penetration rate (PR) are depicted in the **Figure 15**. As expected, the higher the PR whereby more travelers are incentivized, the higher energy savings per person will be. In another word, when a traveler uses Tripod, he/she is fed with the information and encouraged by tokens; thus, his/her average energy consumption will be less than traveling with no information and tokens awarded. By getting deeper in the presented results, a decreasing trend is observed in the energy consumption values changing while the PR increases. For instance, an additional 4% savings is achieved when the PR increases from 50% to 75%, while an additional 2.5% savings is achieved when the PR increases from 75% to 100%. This can be justified by the Saturation Effect concept where the congestion is increasing since more travelers are using the network. In case of Tripod user, the energy consumption trend will be decreasing but its descending speed reduces over time due to the herein mentioned increasing congestion, which in turn increases the energy consumption in comparison to light traffic conditions. In the **Figure 16** the average personal energy consumption changes as a function of PR is demonstrated (different from the left side of the graph which shows energy consumption trend per trip). For better exploration or the results, they are broken down by major modes such as drive alone, bus and carpool. Regarding the graphs, the average personal energy consumption decreases for all three major modes while the PR increases. For the two private vehicle modes (drive alone and carpool), the mentioned trend is because of improved traffic conditions, as more travelers shift to the bus mode, which lowers the travel time. So, the less the vehicle-based trips occur, the less energy consumption per Tripod user. Furthermore, the average personal energy consumption for the bus mode is decreasing as well due to higher bus ridership. Because the bus energy consumption is constant, since the bus schedule is exogenous in the system and is independent of number of riders and incentives, the more travelers shift to the bus and the less their personal average energy consumption will be. "Observe that mode switching is not the only source of energy saving: even the users who drive alone may contribute energy savings by taking more energy-efficient routes." [3]

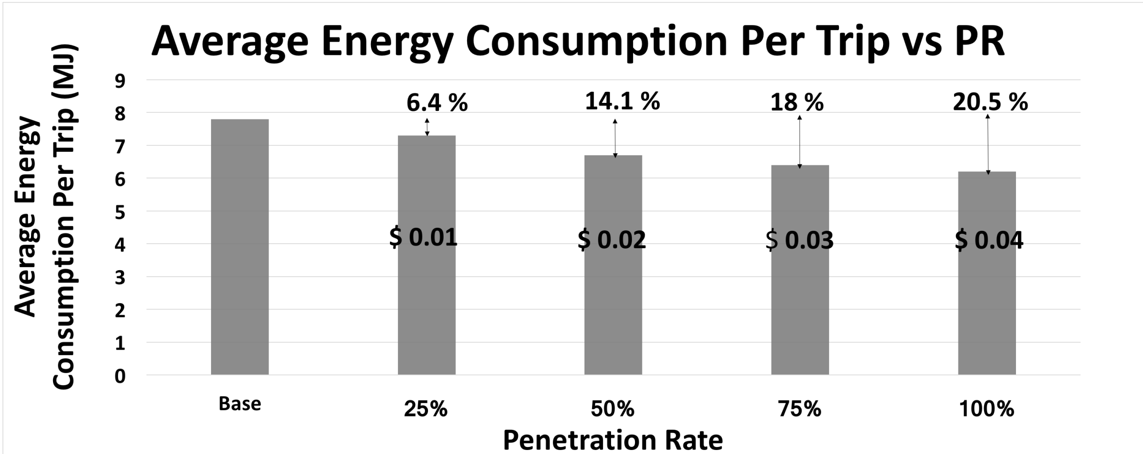

Figure 15: Overall Average Energy Consumption per Trip

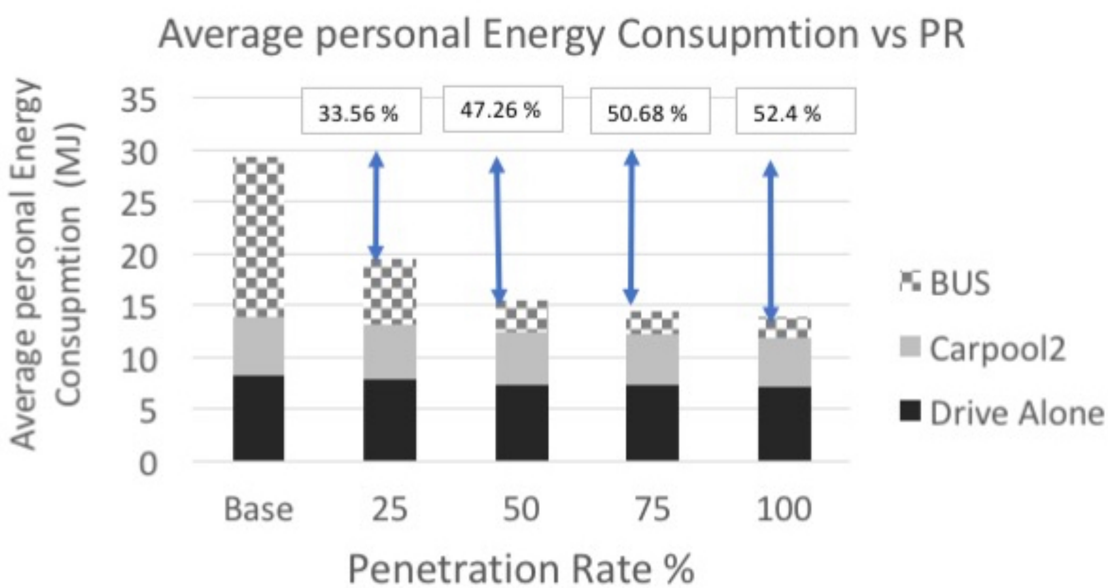

Figure 16: Mode-specific Average Energy Consumption per Trip

As per **Figure 17**, the average personal travel time change is presented versus the increasing penetration rate (PR) of Tripod. Noting that minimizing the travel time is not the objective function of Tripod optimization, such an increasing trend in average personal travel time is not an unanticipated outcome. Tracking the changes for each of the major travel modes and breaking down the results with respect to bus, carpool and drive-alone modes, declares a descending trend in the average personal travel time for two private modes (drive-alone and carpool) while the PR increases while that of the bus is increasing. The former trend is justified with the mode shifting whereby fewer vehicles are on the road resulting from shifting to more efficient modes, like the bus, walk and bike. Noting that travel time of a bus rider includes access, egress and in-vehicle travel time, the increasing trend is due to more travelers being incentivized to take bus, despite the longer access and egress times. By averaging the personal travel time over the whole network, not mode-breakdown results, it will be derived that at lower PRs, the overall average travel time is lower since users are not exposed to the incentives and information. Consequently, private modes, carpool and drive-alone, have a higher share throughout the entire network which in turn decreases the overall average travel time per each traveler as the travel time between the origin and destination matters not the access and egress times. The more travelers use Tripod, the higher PR will be and the higher the overall average travel time per traveler since shifting from private modes to bus increases and its large travel time dominates. Although the personal average travel time increases because of shifting to bus mode, it should be noted that "those who switch to transit and thus have increased personal travel times, do so at their own will which illustrates the fact that they have switched indicates that they perceive the incentives more than compensate for their losses in their travel time." [3]

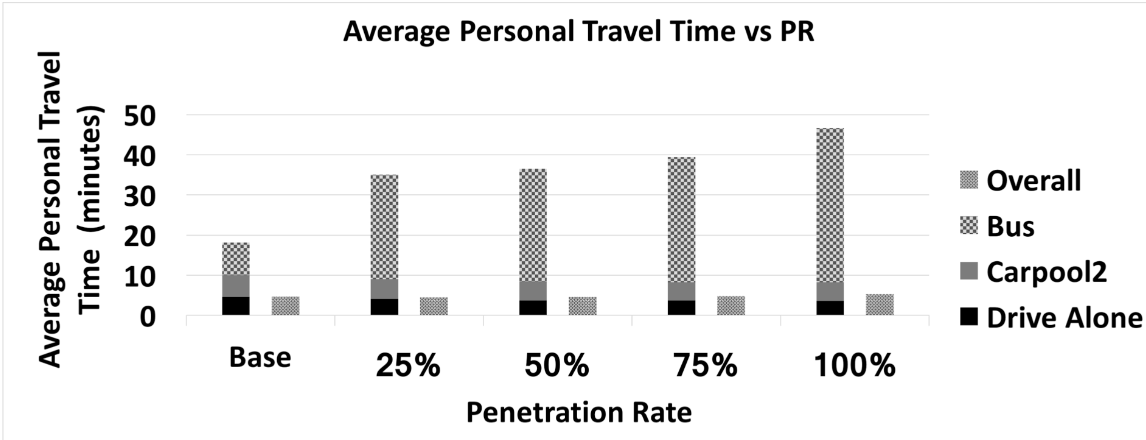

Figure 17: Average Personal Travel Time

Figure 18 depicts the results of token consumption changes as a function of PR in Tripod users, broken down by major modes of drive-alone, carpool and bus. As expected, the more travelers use Tripod, the higher penetration rate, the more tokens will be assigned, and token consumption increases. Through ordering the modes regarding their token consumption, carpooling takes the first rank followed by the bus and the drive-alone stand at last. The herein mentioned ordering implies the attractiveness of the modes from the user's perspective. Carpool is the most pleasing mode and drive-alone is the least pleasing. Carpool and bus modes have roughly the same energy-saving potential, though carpooling is yet more appealing to the travelers due to its better travel time. On the other hand, the Drive-alone mode has the least token consumption because of its very low energy-saving potential through route choice. In addition, the average monetary values, which are perceived by the travelers through the tokens consumed per each trip, are also depicted in **Figure 15** above the bars. In order to obtain the monetary values, the number of tokens per trip is required for which the total number of distributed tokens is divided by the number of trips. The $0.50 per token is assumed and is used for finding the average monetary value of tokens consumed. Moreover, for proving the efficiency of Tripod, the "Tokens per Tripod trip" is also calculated. A Tripod trip stands for the trip of a traveler who accepted one of Tripod's provided options and earned tokens which can be specified with trips having positive tokens consumed value. The perceived monetary values of tokens per Tripod trip are as follows: $2.45, $2.68, $2.76 and $2.86 for penetration rates of 25%, 50%, 75% and 100%, respectively, and these values are considerably higher than their corresponding value with the same PR.

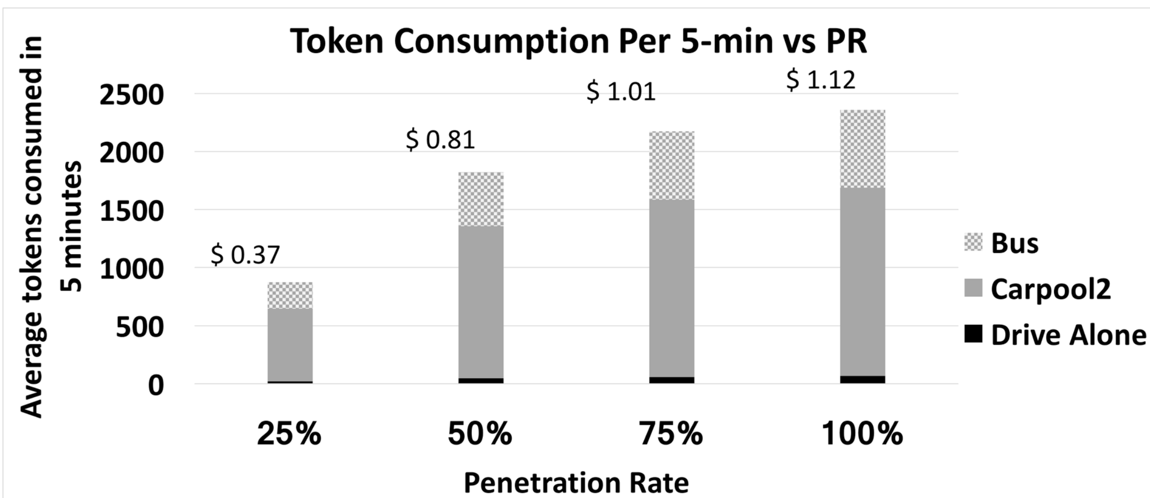

Figure 18: Token Consumption per 5 minutes. The number above each bar is the average perceived monetary value of tokens per trip

As per the top of **Figure 15**, the monetary values of energy savings are shown as numbers on the bars and all are estimated by assuming the fuel price as of $3/gallon. "It should be noted that the perceived monetary value of a token is different from the cost of providing the token, e.g., if the tokens are exchanged for goods as in-kind gifts from participating vendors, the cost of the token to public is in fact 0. Similarly, the cost saving from a consumption reduction of one gallon of fuel, is not necessarily the same as the prevailing market price, if the goal is to evaluate the societal cost of consuming one gallon of fuel, especially when the market does not have an adequate mechanism to reflect the external costs of fuel consumption such as environmental costs. Therefore, these values are presented for information purpose and should not be used directly to do a benefit-cost analysis." [3]

4.4 Closed-loop results with route/departure time choice in CBD

Table 3: Preliminary Closed loop results with Route and Departure Time choice in CBD

Penetration Rate	Average Energy Consumption Per Trip (MJ)	Energy Saving Per Trip	Average Travel Time (second)	Travel Time Saving Per Trip
0 (base case)	9.2	N/A	458	N/A
25%	9.0	2.1%	442	3.5%
40%	8.7	5.4%	409	10.7%
50%	8.7	5.4%	417	9.0%
60%	8.7	5.4%	413	9.8%
75%	8.6	6.5%	420	8.3%
80%	8.6	6.5%	420	8.3%

In closed-loop results, the measures of effectiveness (travel time and energy consumption) are calculated from SM, instead of from SO. "**Table 3** shows preliminary close-loop results in the Boston CBD network with the same settings as in the open-loop tests (Section 4.2). A trend in energy saving similar to that in the open-loop result (**Table 1**) is observed, where the energy saving increases with the penetration rate of Tripod, and the increases flattens out as the penetrate rate increases. Travel time savings are also observed. However, they do not follow a certain pattern. Further tests and analyses will be carried out to understand the intricate relationships between energy consumption and travel time at a system level." [4]

4.5 Performance of on-line optimization:

Noting that an implemented on-line optimization strategy is dynamic which re-computes the TEE $e(t)$ over time to adapt to the network evolution, and its benefits are depicted in **Figure 19**. As per the previous discussions, several instances of DynaMIT are used to do the optimization, for the obtained results *M = 8* instances were employed. A logarithmic search methodology is implemented to look for candidate TEEs within the lower and upper bounds, as of 1 and e_{MAX} = 2000, respectively and to assign them to each instance *m = 0,1, …., M-1* a candidate TEE $e^m(t)$ such that $\ln e^m(t) = m \times \frac{\ln e_{MAX}}{M-1}$ which results in the following set of discrete values: $\{1,3,8,26,77,228,675,2000\}$. The overall energy consumption of the on-line optimization is compared with that of the several "Static allocation" cases within **Figure 19**. The Static allocation stands for the case in which the *e(t)* does not change along the time and is set to a constant value from the above-mentioned discrete set of TEE candidates. "Note that, in reality, in order to implement a static TEE policy, only one static allocation can be implemented at a time and it is impossible to know in advance what the best value is to apply. On the contrary, the on-line optimization does not require this a-priori knowledge, it adapts automatically to the current conditions of the network, guaranteeing energy saving." [3]

"It should be pointed out that the optimization is quite demanding in terms of computational resources. However, at least in the considered scenario, with a 5 minutes roll period and a 15 minutes prediction horizon, the framework has shown to be scalable, i.e., the entire mentioned SO operations have been performed in real-time. This means that the computation of the next TEE value, pertains to the next roll period, can be completed at the current roll period before the beginning of the next one. The machine used is a PowerEdge T630, equipped with two Intel Xeon E5-2695 v4 2.1 GHz processors, 128 GB of memory and an SSD disk.” [3]

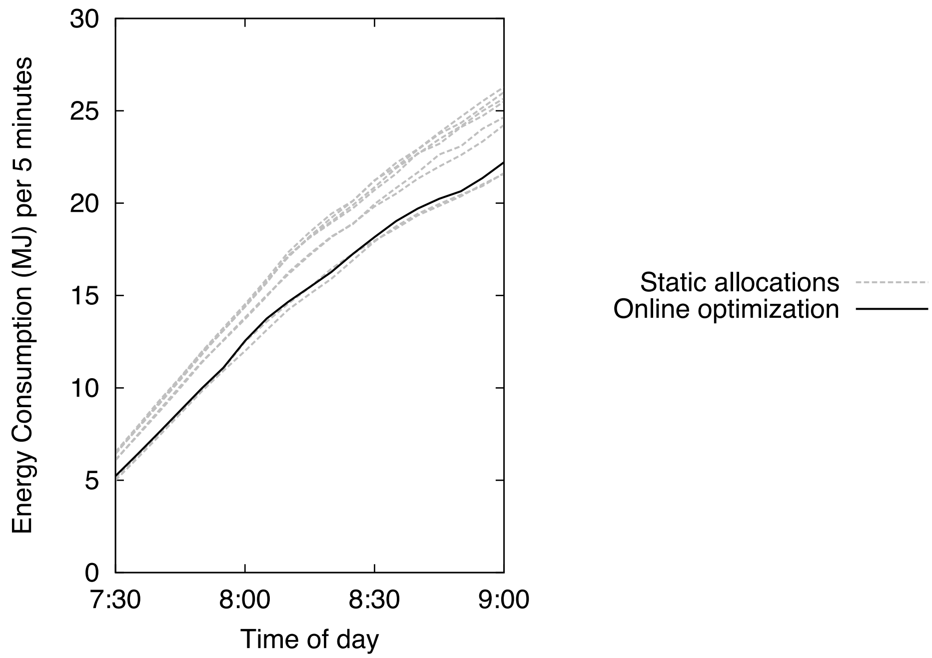

Figure 19: On-line optimization vs. static allocations

CHAPTER 5

CONCLUSION

This implementation of Tripod's [15] optimization network is described in the current research. Tripod is a "novel demand management system which incentivizes travelers in real-time to reduce the system-wide energy consumption of a transportation network, under an incentive budget constraint. The major challenge is dealing with a sophisticated optimization problem since it is on-line, includes several modes of transportation, computes personalized incentives, is guided by both the current and predicted states of network. In order to deal with and reduce this complexity, a heuristic method is implemented as a proposed methodology whereby the problem is simplified to search for a single value, called Token Energy Efficiency, TEE. Predictions are based on multimodal traffic simulation and models of individual travel decision making, including the response to be incentivized. Simulation results reveals that this system is potentially effective in reducing the energy consumption under different scenarios and that large benefits come from the dynamic nature of the on-line optimization." [3]

"Although Tripod's potential for a specific setting is elaborated, the analysis has some limitations such as: *i)* a small network, which does not capture the full extension of travel patterns, network complexity and computational burden of large networks, *ii)* the morning peak period is not being taken into account, thus ignoring some behavioral time-dependencies in individual decision making and the budget allocation across longer periods, *iii)* a single configuration of Tripod is being used, as one can easily design a system with different user segment participation rate, menu generation constraints, a relaxation in having just a single token energy value or even subsets of choice dimensions to be incentivized and *iv)* a single system objective of energy saving while other viable objectives like travel time saving and reliability improvement are not accounted for. In order to resolve the limitations above, further measurements and implementations are under study to integrate the proposed framework with an agent-based simulator [28] for impact validation and scenario exploration. Field trials are also being pursued to evaluate the feasibility and the effectiveness of Tripod in realistic settings." [3]

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