A Generalized and Dynamic Framework for Solar-Powered Roadside Transmitter Unit Planning

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***Abstract*—Roadside Unit (RSU) planning is a key step for the development of a robust Intelligent Transportation System (ITS). Many factors, including traffic flow variation, energy consumption, and budgetary constraints, all affect the daily operation and performance of the ITS. Therefore, there is an urgent need to effectively incorporate all these factors in designing a planning program that addresses this complex and dynamic problem. In this paper, we propose a general RSU planning solution, where complex and dynamic parameters are investigated. The objective is to maximize the effective coverage area of the placed RSUs, given: i) a planning budget comprised of periodic operating expenses (OPEX) and capital expenditures (CAPEX), ii) the physical limitations of the transceivers, and iii) the potential use of renewable energy to offset the on-grid electricity cost. We formulate a Mixed-Integer Quadratically Constrained Programming (MIQCP) problem that can simultaneously determine the optimal placement and daily activation/deactivation schedules of each RSU, whether or not they have a solar panel attached, and their ranges during each period of time. We performed a sensitivity analysis over a realistic map, and results show that as the budget increases, no matter the CAPEX/OPEX, there is an increase in coverage efficiency with a diminishing-returns behavior, a positive correlation between maximum transmission power ratings on the RSUs and coverage efficiency, and a negative correlation between minimum required data transfer rate and coverage efficiency.**

***Index Terms*—Infrastructure Planning, Intelligent Transportation Systems, Optimization, Roadside Unit.**

I. Introduction

In the last decade, there has been an explosion of interest in connected/autonomous vehicle development, incorporating more devices into the Internet of Things (IoT), and leveraging the ever-growing datasets into useful action plans. The new autonomous and connected vehicles have a whole suite of new technologies [1]. These new features, paired with new high-speed connections to the Internet and new data-processing methods, can be utilized to provide more detailed, accurate, and useful real-time information that can be invaluable for ITS end-users.

The most commonly proposed infrastructure development to incorporate these emerging technologies is to install Dedicated Short-Range Communications (DSRC) units, a.k.a. roadside units (RSUs), alongside the roadways [2]. These short-range transceivers allow for a sufficiently fast data transmission rate between the infrastructure and vehicles passing through its effective range, so all relevant data can automatically be forwarded to the main control system, and vice-versa.

Intelligent Transportation System (ITS) planners face several challenges when it comes to figuring out how to build a robust network of these RSUs that will maximize the effective coverage of their system. First, the RSUs only have a limited effective range [2], which is further effected by transmission channel-loss [3]. Second, there is a finite (and likely small) amount of financial resources that can be budgeted for the RSU installation and operations. Third, both efficient energy consumption and varying traffic flow through certain areas need to be considered in tandem. For instance, it is preferable to place RSUs in areas with higher volumes of traffic so larger amounts of data can be sent through the ITS infrastructure, and returned to the vehicles, or placing RSUs in areas requiring higher monitoring levels to report incidents. During periods of low traffic, RSUs in less busy areas can be switched off to conserve energy, and then switched back on to cope with increased network demand. An effective planning problem will go beyond static installation by considering temporal variations in traffic conditions to ensure that RSUs are installed in optimal locations for the whole day, and also can switch on or off automatically to match time-dependent traffic behavior changes across different time periods.

Previous work has looked at each of the aforementioned factors in isolation, or in less complex settings. In [4], the approach to optimal placement was to formulate the problem as an Integer Programming Knapsack Problem, with the objective to maximize coverage by deciding whether or not to place RSUs, given a set of candidate locations and budget constraints. The authors of [5] designed an RSU placement scheme utilizing movement patterns, rather than analyzing specific trajectories, providing the basis for utilizing a fitness metric to guide placement. In [6], the authors investigated how network performance relates to the effectiveness of coverage (e.g. focusing placement in more useful locations), which provides further justification for the objective selection in our model. The authors of [7] utilized multi-objective approaches to factoring both capital (a.k.a. CAPEX) and operational (a.k.a. OPEX) expenditures and the trade-off between both for placement in the minimization of cost for RSU placement. Finally, in [8], the authors discussed energy-efficient RSU scheduling and placement. Their approach led to the combined installation and scheduling of RSUs, another factor incorporated into the proposed framework. Our approach was to blend all of these factors into a singular framework to aid ITS decision-makers when installing/scheduling RSUs. The authors in [9] explore utilizing a genetic algorithm heuristic algorithm for RSU planning. Although a heuristic will provide a quick result, the solution is suboptimal, which may harm the performance of the system in the long run.

As far as the authors know, the present paper proposes a novel and generic approach to optimally plan, install, and schedule RSU infrastructure for ITS applications. The objective of this approach is to place RSUs in such a way to

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maximize the effective coverage of the transceiver network (configuring them to cover the most important areas defined by a fitness utility metric highlighted in Figure 1), given the budgetary restrictions, trade-offs between installation costs vs. operational costs, physical limitations of the transmitters, local realistic topology of the area of interest, and factoring in renewable energy sources, specifically solar power, which can offset emissions and also reduce OPEX. On the other hand, solar panels will incur additional installation costs, which need to be factored into budgetary considerations as well.

To consider these factors, we formulate a Mixed-Integer Quadratically Constrained Program (MIQCP) to provide a guide for ITS planners on the optimal installation locations of RSUs and solar panels, the daily schedule of activating/deactivating RSUs, the range of the RSUs at each time period, and the financial resources required to implement the solution. We found that the model will readily do this for all given financial parameters, with RSUs following DSRC specifications in urban settings.

Unlike previous work that considered simplified grids, or one-dimensional road networks, the proposed framework is designed to work for any realistic road network. The other models consider either installation or scheduling separately; this framework considers both at the same time. Additionally, our model considers budget, traffic flow, temporal changes, physical transceiver limitations, and renewable energy all at once, rather then considering one or two of these factors separately. The proposed framework is designed to aid in implementation of a Vehicle-to-Infrastructure (V2I) Vehicular Ad-Hoc Network (VANET) for the purpose of automated crowd-sensing applications, including, but not limited to, real-time traffic updates, disruption modeling, data collection/filtration, and emergency response improvements.

In this paper, Section II discusses the development of the system model. Section III describes the formulation of the optimization model, and Section IV discusses the findings, and sensitivity analysis of the model. Conclusions are drawn in Section V.

II. System Model

We consider a complex road network consisting of $K = |\Phi|$ geographic coordinates (e.g. points), where Φ is the set of points in the area of interest, and $|\Phi|$ represents the cardinality of the set (i.e. the number of points considered). These points can either be intersections or along segments of roadways between intersections. The points are identified by their geographic coordinates, and each is characterized by a fitness metric score f_k assigned by the ITS planner, where $k = 1, 2, ..., K$, $k \in \Phi$ denotes the index of each unique point on the map. This fitness metric is calculated by utilizing a weighted additive utility function considering the traffic flow density, accident rate, and/or other various factors pertinent to a traffic system. Our model also considers time-dependent variation in the fitness scores based on traffic flow changes, such as during rush hour, late-night periods, etc. To account for this, we add the index t to consider spatio-temporal fitness scores f_{kt} during time period $t = 1, 2, ..., |T|$, where T represents the set of time periods in the day, and each time period is $\frac{24}{|T|}$ hours in duration.

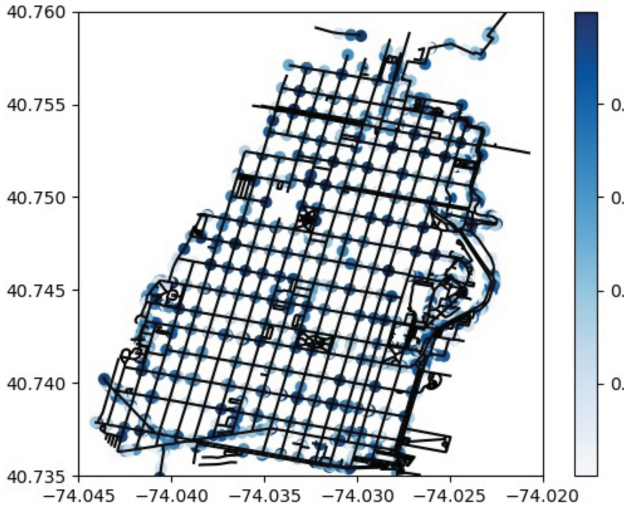

Fig. 1. The road network of Hoboken, NJ, which was utilized to test the model's behavior. The color bar ($[0, 1]$) represents a normalized utility function representing a linear combination of various factors including traffic flow density, accident rate, and other factors that determine how "important" a point is. The black lines are the city's streets.

Our model considers a set of points J that are candidate RSU installation locations, chosen by the ITS planners based on geological, topographical, and right-of-way restrictions. The ITS planners have a set of unique RSU classes I, where $i = 1, 2, ..., |I|$ that they may choose from to install. These different RSU classes each have unique characteristics such as effective range, power consumption, installation costs, etc.

We consider the possibility of installing photo-voltaic solar panels at each RSU that can be used to offset the consumption of electricity from the conventional power grid of each individual RSU. We consider that the number of RSUs and solar panels installed by the ITS operator is dependent on maximizing the utilization of a daily operating budget denoted by $\bar{D}$; this periodic budget includes i) OPEX such as electricity, denoted by γ, and ii) periodic amortized CAPEX of installing RSUs of type i, denoted by c_i, and solar panels, denoted by c_q, where $q \in \Omega$, $q = 1, 2, ..., |\Omega|$ represents different classes of solar panels in the same vain as the different classes I of RSU's.

A. Roadside Unit Power Consumption Model

We assume that the power consumption of the RSU of type i placed at point j and activated at time period t is expressed as follows [10]:

$$P_{ijt}^{tot} = a_i p_{ijt} + b_i, \tag{1}$$

where a_i is the ratio between transmission power and required power to amplify the signal and b_i is energy converted to heat by electrical resistance.[1] The variable p_{ijt} is the transmission power of an RSU of type i placed at a location j during time period t. Its value cannot exceed the maximum power rating, denoted by P_i^{max}, as follows $p_{ijt} \leq P_i^{max}$.

B. Roadside Unit Coverage Model

In our model, we assume that a point k as being covered by an RSU placed at point j if the distance between the two points

[1] Assuming a linear model for the power model has been considered in many previous studies as it approximates the power consumption and simplifies the analyses [10] and [11].

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is less than the range of the transmitter being able to transmit data at a desired throughput R, in Mbps. We derive the RSU range using the channel power loss model [12]. After careful mathematical manipulations, the effective distance threshold d_{th} in meters to have a minimum data transfer rate R given a transmission power p_{th} in Watts is given as follows:

$$d_{th} = 10^{\left(\frac{-PL_0}{10\nu}\right)} \left[\frac{p_{th}}{K_b T B \left[2^{\left(\frac{R}{B}\right)} - 1 \right]} \right]^{\frac{1}{\nu}}, \qquad (2)$$

where PL_0 represents the initial power loss in dBm, ν is the dimensionless channel loss exponent, K_b is Boltzmann's constant, T is the blackbody radiation temperature in Kelvin, and B is the bandwidth in MHz. We manipulate the equation to find the power transmission threshold $p_{th}(j, k, R)$, defined as the minimum transmission power required to achieve a data transfer rate R given the distance between points j and k $d_{th}(j, k)$:

$$p_{th}(j, k, R) \geq \left(K_b T B \left[2^{\left(\frac{R}{B}\right)} - 1 \right] \right) \left(d_{th}(j, k) \left[10^{\left(\frac{PL_o}{10\nu}\right)} \right] \right)^{\nu}. \qquad (3)$$

C. Solar Power Model

The maximum amount of power generated from a solar panel of type q can be expressed as the following [13]:

$$\phi_q^{max} = A_q \Psi \eta, \qquad (4)$$

where A_q represents the surface area of the solar panel of type q in m^2, Ψ represents the solar radiance in W/m^2, and η represents the efficiency of the solar panel. In our model, $\bar{\theta}_{qt}$ represents the average solar power generated during time period t, and can be calculated by the following formula [13]:

$$\bar{\theta}_{qt} = \frac{\phi_q^{max} e^{-(\tau_t - \mu_\tau)^2}}{\sigma_\tau^2} \delta_t, \qquad (5)$$

where τ_t represents the middle time of the time period (e.g. if the time period goes from 12pm to 4pm, $\tau_t = 2\text{pm}$), μ_τ represents the time of day that the peak power generation occurs (e.g. 12pm), σ_τ represents the half-width of half of the peak (e.g. 3 hours), and δ_t represents the duration of the time period t in hours.

III. Problem Formulation

In this section, we formulate an optimization program with the goal of maximizing the effective daily coverage of the installed RSUs, while factoring in the previous considerations we made in Section II.

A. Objective Function

Our objective is to install RSUs in optimal locations such that they maximize the coverage of the points on the map while remaining within the budget. The daily coverage efficiency (%) is defined as:

$$E = \frac{\sum_{k \in \Phi} \sum_{t \in T} z_{kt} f_{kt}}{\sum_{k \in \Phi} \sum_{t \in T} f_{kt}}, \qquad (6)$$

where z_{kt} is a binary value representing whether or not point k is covered by at least one RSU during time period t; $z_{kt} = 1$ if this is true, $z_{kt} = 0$ otherwise.

TABLE I
RSU Planning Primary Decision Variables

Notation	Description	Type
x_{ijt}	**Decision:** Whether or not to place an RSU of type i at potential location j, and whether or not it is activated at time t. A value of 1 corresponds to the RSU of type i activation at point j during time period t, and 0 represents otherwise.	Binary
y_{ijkt}	**Decision:** Whether or not a point k is covered by an RSU of type i at potential location j during the time period t A value of 1 corresponds to a point k being covered by an RSU of type i activated at point j during time period t, and 0 represents otherwise.	Binary
Q_{qj}	**Decision:** Whether or not to place a solar panel of type q at potential location j. Solar panel placement does not have a time index attached, because solar panel placement cannot change on a daily basis. A value of 1 corresponds to solar panel of type q installed at point j, and 0 represents otherwise.	Binary
p_{ijt}	**Setting:** The transmission power setting of an RSU of type i at potential location j, during time period t, and can be any value between 0 (e.g. transmitter deactivated), or its maximum rating P_i^{max}	Continuous

B. Problem Constraints

Our goal of maximizing the coverage efficiency of the RSU network is constrained by the following:

1) Coverage Constraint: The coverage of point k at time period t is based on the following:

$$z_{kt} = OR_{i \in I, j \in J} \left(x_{ijt} y_{ijkt} \right), \forall k, t \in \Phi, T, \qquad (7)$$

where the point k is considered covered at time period t if there is at least one RSU of type i placed at point j activated during time t ($x_{ijt} = 1$), and point k is within the effective transmission range of that RSU ($y_{ijkt} = 1$) based on the coverage model highlighted in Section II-A. A logical $OR_{i \in I, j \in J}$ function is used to prevent double-counting of the point in the objective function (i.e. if the point rests within the transmission range of two or more different RSUs, it is only counted as covered once).

2) Range Constraints: Elaborating further on the definition of a point k being within the RSU transmission range:

$$y_{ijkt} = \begin{cases} 1, & \text{if } p_{ijt} x_{ijt} \geq p_{th}(j, k, R) \\ 0, & \text{otherwise} \end{cases} \quad \forall i, j, k, t \in I, J, \Phi, T. \qquad (8)$$

If the transmission power of an active RSU of type i located at point j during time period t is equal to or greater than the threshold $p_{th}(j, k, R)$ defined earlier, the point k is covered. Also, a point k can only be covered by an RSU type i placed/activated at a point j during time t if an RSU is active at point j:

$$y_{ijkt} \leq x_{ijt}, \forall i, j, k, t \in I, J, \Phi, T. \qquad (9)$$

3) DSRC Specifications Constraint: The transmission power of an active RSU cannot exceed its maximum power rating:

$$p_{ijt} \leq x_{ijt} P_i^{max}, \forall i, j, t \in I, J, T. \qquad (10)$$

4) Budgetary Constraint: The daily budget is based on the daily OPEX and amortized CAPEX for the ITS operator expressed by the following equations:

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} O_{ijt} + C_{ijt} \leq \bar{D}, \tag{11}$$

where

$$O_{ijt} = x_{ijt}(\max\{((a_i p_{ijt} + b_i) - \sum_{q\in Q} Q_{qj}\bar{\theta}_{qt}), 0\})\gamma \tag{12a}$$

$$C_{ijt} = c_i x_{ijt} + \sum_{q\in Q} c_q Q_{qj}. \tag{12b}$$

O_{ijt} is the OPEX of an RSU of type i, placed at a location j during time slot t as a function of the RSU power consumption $x_{ijt}(\max\{((a_i p_{ijt} + b_i) - \sum_{q\in Q} Q_{qj}\bar{\theta}_{qt}), 0\})\gamma$, where γ represents electricity expenses. The parameter C_{ijt} is the per-time-period amortized CAPEX of installing an RSU $c_i x_{ijt}$ and/or a solar panel $c_q Q_{qj}$. We use the max function for the solar power offset to count only the on-grid electricity cost and avoid a situation where the marginal OPEX makes the budget incrementally larger by taking negative values.

5) Uniqueness Constraint: To ensure uniqueness of RSU placement, at most only one RSU of type i can be placed at a point j can be activated/installed at time period t:

$$\sum_{i\in I} x_{ijt} \leq 1, \forall j, t \in J, T, \tag{13a}$$

$$\sum_{j\in J} x_{ijt} \leq 1, \forall i, t \in I, T. \tag{13b}$$

6) Time Consistency Constraint: To match demand fluctuations of traffic in the area, RSUs can be turned on or off in order to further conserve electricity. One thing to keep in mind - the time periods in T are *not* ordered chronologically, they are ordered in ascending order of overall network activity - rush hour periods would likely be the highest-indexed time periods, and late-night periods would likely by the lower-indexed time periods, for example. Since we order the time periods from times with least overall demand to most overall demand, the RSUs active during less busy time periods must remain on during busier time periods:

$$x_{ijt} \leq x_{ij(t+1)}, \forall i, j, t \in I, J, T \setminus |T|. \tag{14}$$

C. Solar Panel Consistency Constraints

In this problem setting, solar panels may only be placed at locations where an RSU has been installed:

$$q_{qj} \leq \sum_{t\in T}\sum_{i\in I} x_{ijt}, \forall q, j \in Q, J, \tag{15}$$

and only at most one solar panel may be placed at a location:

$$\sum_{q\in Q} q_{qj} \leq 1, \forall j \in J, \tag{16}$$

After solving the problem, when the time periods are reordered chronologically, the values of x_{ijt} form a daily schedule for RSU activation/deactivation. Note that this is a proactive on/off switching planning of the RSUs. Real-time and instantaneous on/off switching of RSUs can still be applied for the active RSUs depending on the instantaneous parameters of the road network.

D. MINLP Formulation

Recall our objective formulated in Section III-B; to maximize coverage efficiency and given all of the above constraints, the optimization program takes the following form:

$$\textbf{max} \sum_{k\in\Phi}\sum_{t\in T} z_{kt} f_{kt}$$

s.t. Equations (7) through (16),

where, without loss of generality, we can remove the sum of the fitness term in the denominator, because it is a constant value. This program is a Mixed-Integer Nonlinear Program (MINLP). The MINLP form is incredibly expensive computationally to solve, and no exact methods exist to optimally solve such a problem in a reasonable amount of time [14]. Therefore, we need to reformulate the problem in a different way in order to utilize an off the shelf solver software such as the Gurobi MIP solver[2].

E. Model Reformulation to MIQCP

We proceed to reformulate the problem as a Mixed-Integer Quadratically Constrained Program (MIQCP), as the Gurobi solver can find the optimal solution for this type of problem utilizing techniques to minimize the candidate pool of solutions as a focused search, such as branch-and-bound, cutting planes, and model presolve [14]. Gurobi also takes advantage of computational parallelism and hyperthreading by distributing subproblems across each processor core.

1) Coverage Constraint Reformulation: Equation (7) is converted to:

$$z_{kt} \leq \sum_{i\in I}\sum_{j\in J} x_{ijt} y_{ijkt}, \tag{17a}$$

$$z_{kt} \geq x_{ijt} y_{ijkt}, \tag{17b}$$

because the $OR_{i\in I, j\in J}$ was nonlinear and non-quadratic; the new equations are now quadratic.

2) Range Constraint Reformulation: Equation (8) is a conditional, and therefore nonlinear function. We approximate it utilizing the Big-M method:

$$p_{ijt} x_{ijt} \geq p_{th}(j, k, R) - M(1 - y_{ijkt}), \tag{18a}$$

$$p_{ijt} x_{ijt} \leq p_{th}(j, k, R) + M(y_{ijkt}). \tag{18b}$$

3) Budget Constraint Reformulation: Equation (11) is converted to:

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}(x_{ijt} r_{ijt} + (c_{ir} x_{ijt} + \sum_{q\in Q} c_q Q_{qj})) \leq \bar{D}, \tag{19}$$

where

$$r_{ijt} \geq ((a p_{it} + b) - \sum_{q\in Q} \bar{\theta}_t Q_{qj})\gamma), \tag{20a}$$

$$r_{ijt} \leq (1 - s_{ijk})((a p_{it} + b) - \sum_{q\in Q} \bar{\theta} Q_{qj})\gamma), \tag{20b}$$

$$r_{ijt} \geq 0, \tag{20c}$$

because the max function made the linear $a_i p_{ijt} + b_i$ component of the OPEX function nonlinear. We introduce the continuous dummy variable r_{ijt} and binary dummy variable s_{ijt} to linearize the max function.

[2]Gurobi Optimization, Inc., *Gurobi Solver 8.01*. [Software]. Houston, TX, USA, 2018.

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4) MIQCP Formulation: The altered model implemented in the solver takes the following form:

$$\max \sum_{k\in\Phi}\sum_{t\in T} z_{kt} f_{kt}$$
$$\textbf{s.t.} \text{ Equations (9), (10), (13) through (20).}$$

Note that this problem will be solved once for the specific planning time horizon, therefore the complexity of the problem is not a critical issue. Nevertheless, due to the NP-hard complexity of the reformulated problem [14], as the size of the set of points Φ considered for the problem grows, the time to solve can grow quite explosively. Even though the problem is NP-Hard, numerical methods discussed in Subsection III-D can be utilized to find the optimal solution for the reformulated MIQCP. If the problem grows to a size where the software still takes an unreasonable amount of time to solve, the ITS operator can adjust by breaking the map into sub-areas $A_1, A_2, ...$ where $A_1, A_2, ... \subseteq \Phi$, and optimally solve each sub-area separately. Hence, a MIQCP is solved for each sub-problem, and the results can be combined to provide an RSU installation plan and daily schedule for the whole area. Another approach could be to utilize heuristics such as evolutionary algorithms to achieve fast, but sub-optimal solutions.

IV. Selected Numerical Results and Discussion

In this section, we discuss the parameters chosen for our initial model run, numerical results, sensitivity analysis on the model, and interpret the meaning of the results. We gathered our road network data from the OpenStreetMap project[3], and used Gurobi 8.01 to solve the MIQCP.

Table II displays the parameters utilized for our initial model run. Recalling the map of Hoboken, NJ in Figure 1, for tractability, we limit the scope of our optimization to a subset of the points on that map. We utilize this small region (Latitude -74.040 to -74.030 and Longitude 40.740 to 40.750), with 213 points, due to the NP-Hard complexity of solving a MIQCP. Note that our map has points primarily on intersections - this model would work if points along the stretches of road were also considered.

Since we split the day into six time periods ($|T| = 6$) of four hours in durations, we use a simplified set of $\bar{\theta}_{qt}$ values that reasonably approximate the amount of solar energy generated. We assume that, in the area of interest, there are 15 candidate locations ($|J| = 15$) to install RSU's of the 213 points ($|\Phi| = 215$) as follows: $k = 0, 15, 30, 45, ...210$.

The path loss exponent ν is assumed to be 3 [3]. We choose three types of RSU, and one type of solar panel, and we utilize uniform random distributions to generate the fitness values for each time period - where the lower and upper bounds of the random number generator varied from each time period in a way that would ensure that the overall fitness score of each time period would increase.

In our initial run, we found that the model performed several key tasks. The model will place RSU's based on fitness throughout the day, will deactivate RSU's during less busy parts of the day, will place solar panels, and will even adjust the transmission power of each RSU to compensate for changes in traffic behavior.

TABLE II
Initial Model Run Parameters

Parameter	Value	Unit
$\|\Phi\|$	215	N/A
$\|J\|$	15	N/A
$\|I\|$	3	N/A
$\|Q\|$	1	N/A
$\|T\|$	6	N/A
$p_{max,i}$, $\forall i$	0.1125, 0.28125, 0.5625	W
f_{kt}, $\forall k, t$	[0,1]	Utility
γ	0.0738	$/hr
c_{ir}, $\forall i$	0.0002, 0.0004, 0.0008	$/hr
c_q, $\forall q$	0.0002	$/hr
$\bar{D}$	1.00	$/6hr
$\bar{\theta}_{qt}$, $\forall q, t$	0, 6, 12, 18, 24, 30	W
R	6	Mbps
B	10	MHz
ν	3	Dimensionless
$a_i, \forall i$	10	Dimensionless
$b_i, \forall i$	5	W

In Figures 2(a)-(d), we visualize a selection of the results from the initial run. In the plots, the red triangles represent active RSUs, gray circles represent the RSU coverage zone, black dots represent covered points, green points represent locations with installed solar panels, with deactivated RSUs at that time period, and blue/white points represent uncovered points. The color bar on each figure corresponds to the fitness scores, where as the points get to be a darker blue, the fitness score is increasing. Figure 2(a) represents the solution from the late night/early morning time period ($t = 0$), which has the lowest traffic flow and therefore lowest overall fitness score. Only one RSU is active in this time period. Figure 2(b) represents the morning rush-hour period, which has the second-highest traffic density ($t = 4$), and 11 active RSUs. Figure 2(c) represents the afternoon/evening rush-hour period, the most active traffic period of the day ($t = 4$), similar to the morning rush-hour period, all 11 RSUs are active. Figure 2(d) represents the later evening, where traffic density is high, but not as high as the rush-hour period in figure 2(c) ($t = 1$), to adjust, the RSUs all have their transmission power settings lowered to conserve energy. In $t = 0$, only one RSU is active, with a high transmission power setting, and all others are deactivated due to the low volume of active traffic. As the streets become busier, the radius of this active RSU shrinks, and other RSUs are activated, to adjust for the daily traffic fluctuations. Due to the low amortized CAPEX, every installed RSU has a solar panel attached as well.

To test the robustness of the model, we solve the problem with a range of values for $\bar{D}$, c_{ir}, c_q, γ, R, and P_i^{max}. Figure 3 focuses on the effects of the entire day coverage efficiency versus the financial parameters. To simplify the sensitivity analysis, we assume that a type II RSU is twice as expensive as a type I, a type III RSU is twice as expensive as a type II RSU, and a solar panel costs the same as a type I RSU to install. We introduce another parameter c_m, which represents the CAPEX multiplier. For example, consider that, in our initial run, $c_m = 0.0002$. From this CAPEX, multiplier, and the previous cost relationships, we came up with the following

[3]Openstreetmap. [Online]. Available: https://www.openstreetmap.org

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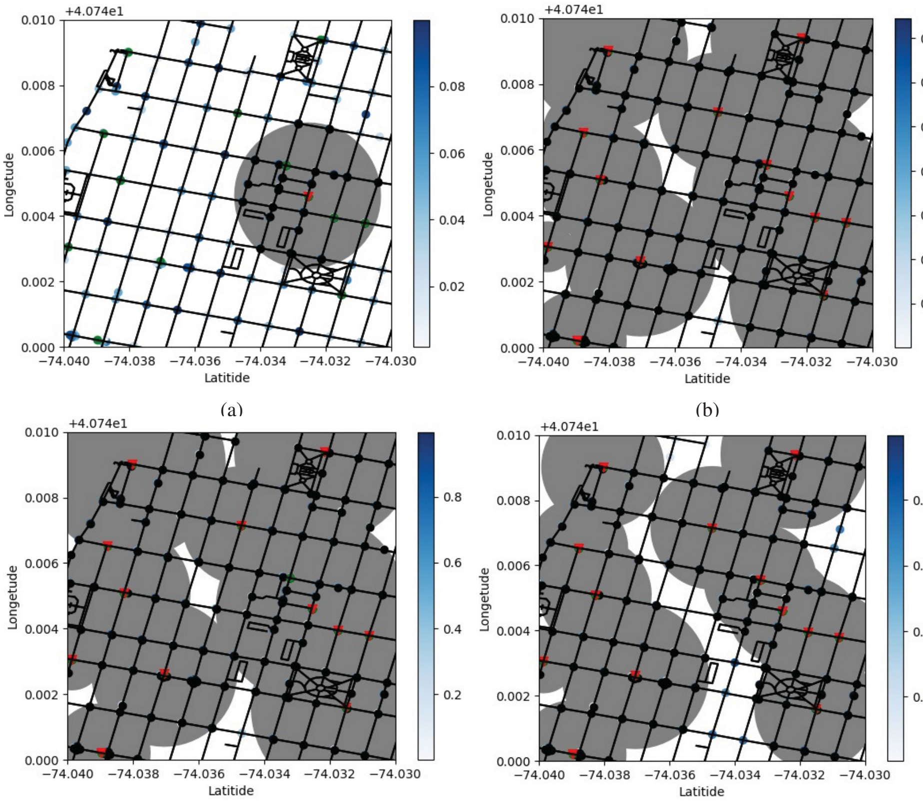

Fig. 2. Visualizing the initial run solution. (a) time period $t = 0$ $\big([3\text{am}, 7\text{am}]$ and $E = 20.4\%\big)$, (b) time period $t = 4$ $\big([7\text{am}, 11\text{am}]$ and $E = 99.2\%\big)$, (c) time period $t = 5$ $\big([3\text{pm}, 7\text{pm}]$ and $E = 99.3\%\big)$, and (d) time period $t = 1$ $\big([11\text{pm}, 3\text{am}]$ and $E = 93.1\%\big)$.

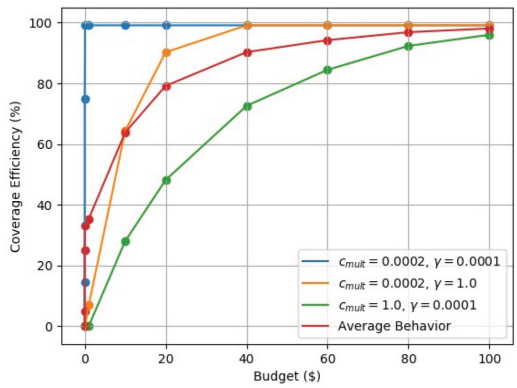

Fig. 3. Financial Sensitivity Analysis. Positive, monotonic, diminishing returns relationship between daily coverage efficiency and budget.

relationships:

$$c_{ir} = \begin{cases} c_m, \text{ if } i = 0, \\ 2c_m, \text{ if } i = 1, \text{ and } c_q = c_m. \\ 4c_m, \text{ otherwise.} \end{cases} \tag{21}$$

In our financial parameter sensitivity analysis, we consider the coverage efficiency vs. budget given three sets of values for γ and c_m: 1) $\gamma = 0.0001$ and $c_m = 0.0002$, 2) $\gamma = 1.00$ and $c_m = 0.1$, and 3) $\gamma = 0.0001$ and $c_m = 1.00$. Figure 3 shows that no matter the variation in parameters, there is a general diminishing returns effect (e.g. as the budget increases, in general so should the coverage efficiency, however the gains in coverage efficiency quickly drop with budgetary increases), an expected result. We also find that as the per-period expenses in either category rises, the diminishing returns behavior becomes less pronounced, another expected result. In general, for a very wide range of financial parameters, the model will produce a tractable result.

Similar to how we simplified analysis of the CAPEX, we simplified analysis of the p^{max} values by utilizing a multiplier p^{mult}, based on the following relationship:

$$P_i^{max} = \begin{cases} \frac{1}{10}p^{mult}, \text{ if } i = 0, \\ \frac{1}{4}p^{mult}, \text{ if } i = 1, \\ \frac{1}{2}p^{mult}, \text{ otherwise.} \end{cases} \tag{22}$$

In our initial run, $p^{mult} = 1.125$. In our technical parameter sensitivity analysis, we consider the number of RSUs active in time period $t = 5$ (the rush hour period where all installed RSUs are activated) and the whole-day coverage efficiency vs p^{mult}, and we consider the number of installed RSUs and the coverage efficiency vs R, for two budgets $\bar{D} = 0.1$ (Figures 4(a) and 4(b)), and $\bar{D} = 1.0$ (Figures 5(a) and 5(b)). We find that as the power multiplier increased, the optimizer is more likely to place type I RSUs, and the coverage efficiency increased. We also find that as the minimum required data rate increases, the coverage efficiency (in general) decreases.

Our numerical results show that the model is feasible for almost every combination of financial parameters, which directly correspond to the coverage, as a larger budget does correlate with more overall coverage. We also found a diminishing-returns effect in the financial sensitivity analysis, showing that after a certain point, the benefits of increased financial input into the system become negligible. The technical parameter

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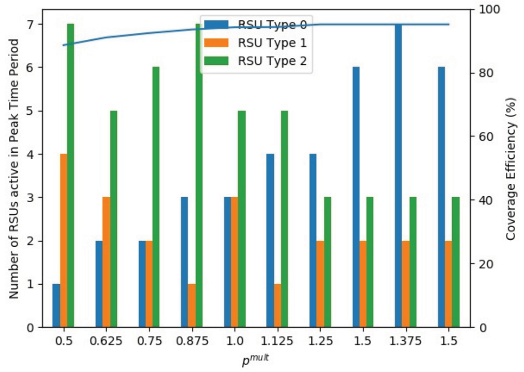
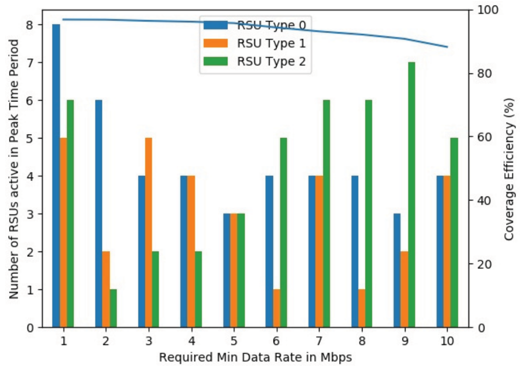
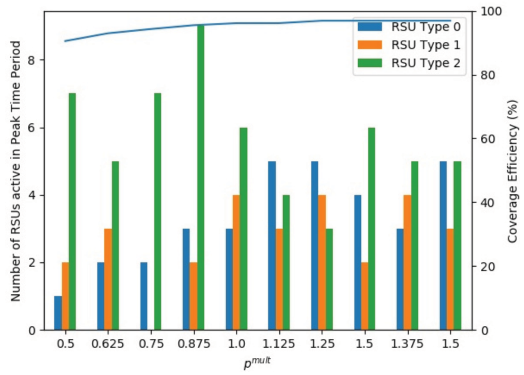


(a)

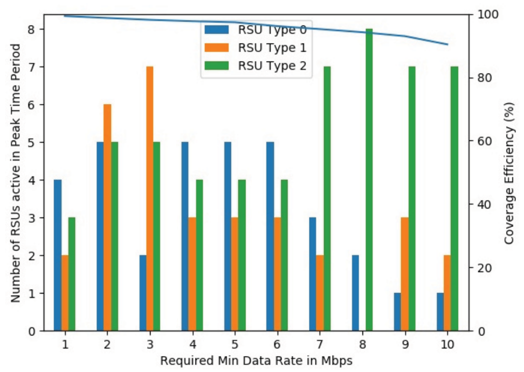


(b)

Fig. 4. Technical Sensitivity analysis with a low budget, (a) the set of model runs with a varying P^{mult} value for $R = 6$ Mbps, and (b) the set of model runs with a varying R value for $P^{mult} = 1.125$.



(a)



(b)

Fig. 5. Technical Sensitivity analysis with a high budget, (a) the set of model runs with a varying P^{mult} value for $R = 6$ Mbps, and (b) the set of model runs with a varying R value for $P^{mult} = 1.125$.

analysis showed that the maximum power ratings for RSUs and minimum data transfer requirements will affect how effective the system coverage is.

V. Conclusion

In this paper, we proposed a framework for optimal energy-efficient RSU deployment and daily scheduling, and looked at a subset of the possible combinations of parameters that could influence the decision provided by it. This proposed framework provides ITS planners the ability to consider budget, time-variation in traffic, renewable energy, and RSU scheduling all at once, helping simplify a highly complex decision for planners. Optimal placement of RSU's in a road network is only the first step - this model will act as a starting point for more complex ITS infrastructure to be built around it, be a benchmark for future planning heuristic alternatives that are developed, and provide a basis for data collection systems that will aim to improve transportation infrastructure utilization, aid in improvement of disruption response, and propagate useful information back to end-users.

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