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RESEARCH ARTICLE

ENERGY MANAGEMENT MODEL FOR INTELLIGENT TRANSPORTATION SYSTEM

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ABSTRACT

Energy saving technologies for smart vehicles have great importance because of decreasing total energy consumption. It is estimated that the cost of energy will increase in the near future. Here, Road Side Units (RSUs) are the dominant contributing components to the overall energy consumption in Intelligent Transportation Systems (ITS). This paper investigates the energy efficiency of RSUs by proposing an energy management model for ITS. Energy efficiency can be achieved if as many as possible RSUs switch off while maintaining an acceptable quality of service. The aim is to present a way to improve total energy efficiency by scheduling RSUs with a switching on/off model so that total energy consumption of RSUs can be managed.

Keywords: *Energy Management, Smart Cities, Intelligent Transportation System, Kriging.*

AKILLI ULAŞIM SİSTEMLERİ İÇİN ENERJİ YÖNETİMİ MODELİ

ÖZ

Akıllı araçlar için enerji tasarruflu teknolojiler, toplam enerji tüketimini azalttığı için büyük öneme sahiptirler. Akıllı Ulaşım Sistemleri'nde, Yol Kenarı Baz İstasyonları toplam enerji tüketiminde en fazla etkiye sahiptirler. Yakın gelecekte, enerji maliyetinin de artması beklenmektedir. Bu kapsamda, Akıllı Ulaşım Sistemleri'nde bir enerji yönetim modeli önererek, Yol Kenarı Baz İstasyonlarının enerji etkinliği araştırılmaktadır. Enerji verimliliği, maksimum sayıda Yol Kenarı Baz İstasyonlarının kapatılması ile sağlanabilir, ancak önerilecek modelin servis kalitesini düşürmeden etkin bir şekilde yönetilmesi gerekmektedir. Bu kapsamda, Yol Kenarı Baz İstasyonlarının enerji tüketimini azaltmak için Yol Kenarı Baz İstasyonlarının kullanımını planlayan bir model geliştirilmesi amaçlanmıştır.

Anahtar Kelimeler: *Enerji Yönetimi, Akıllı Şehirler, Akıllı Ulaşım Sistemleri, Kriging.*

1. INTRODUCTION

The expansion of smart city technologies creates both challenges and opportunities in Intelligent Transportation Systems (ITS). On one hand, smart vehicles can communicate with each other and provide high quality data to prevent accidents and increase traffic safety. On the other hand, any interruption in a service is essential. In particular, it is a challenge to meet Quality of Service (QoS) of a task in smart vehicles because of the mobility and limited communication range of RSUs.

One of the earliest technological advances was the ability of equipped with onboard units (OBUs) of vehicles. The U.S. FCC (Federal Communications Commission) has allocated 75 MHz in the 5.9 GHz frequency band for Dedicated Short Range Communication in 1999. With the recent advances in smart city technologies and rapid growth of mobile communications and devices, vehicles are designed to increase situational awareness and improve traffic safety, efficiency and comfort. Vehicles are equipped with advanced technologies in order to communicate with nearby vehicles and Road Side Units (RSU) in ITS.

Energy saving technologies for smart city have been widely studied in order to manage increasing data traffic and decrease total energy consumption. Here, RSUs are the dominant contributing components to the overall energy consumption in ITS. It is estimated that the cost of energy will increase in the near future and it is crucial to keep the supply-demand balance [1]. Therefore, in order to improve energy efficiency of RSUs, the position of RSUs and their coverage areas have a great importance. There exist many vehicular applications that can be effectively used in ITS for many purposes. However, many challenges significantly limit the performance of these applications such as task allocation of RSUs and task execution by considering energy constraints.

While the basic task of ITS is quite simple-enabling communication between vehicles and RSUs, the connectivity is needed to achieve this basic task. In [2]-[3], the challenges of ineffective resource allocation and RSU overload are investigated in ITS. In [4]-[5], power control mechanisms are proposed to increase energy efficiency. Although many approaches have been proposed in the literature to address the challenges of energy consumption and connectivity, none of these approaches provides a management to decrease energy consumption with the help of power estimation mechanism.

To this end, this paper focuses on reducing energy consumption of RSUs in ITS. To achieve this, an energy management model is presented for ITS. In the model, minimum number of active RSUs is determined to serve all vehicles on the road. Depending on the distribution of vehicles within the communication range of each RSU, vehicles are assigned to particular RSU and then the number of active RSUs is minimized. To achieve this, a controller estimates the power level of vehicles with a spatial estimation method. Kriging is used to find the appropriate signal levels of vehicles so that RSUs are managed efficiently. Here, the location of vehicles, velocity and heading are given to the proposed model as an input. Then, the controller decides the mode of each RSU to reduce energy consumption.

The remainder of this study is organized as follows: Section 2 defines the considered scenario and model development. Section 3 gives the used data and methodology. Section 4 evaluates the results of the proposed model and finally Section 5 concludes the paper.

2. MODEL DEVELOPMENT

RSUs are deployed along the road in order to serve the vehicles within the coverage areas as seen in Figure 1. Vehicles can only connect one single RSU at a time. The controller takes the vehicle information as an input including vehicle location, velocity, heading, distance between vehicle and RSU and signal level. IEEE 802.11p based communication is used for V2R (Vehicle-to-Road Side Unit).

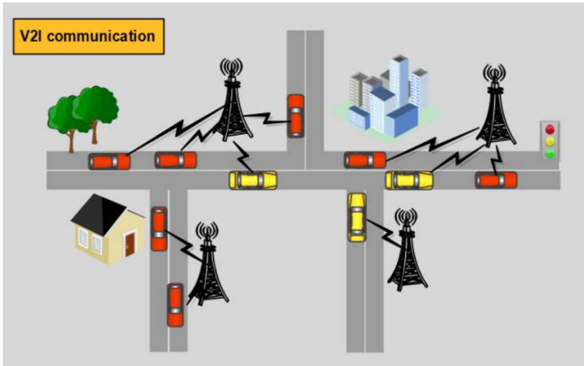


Figure 1. The considered architecture.

In the paper, the aim is to manage RSUs by controller so that the mode of RSUs can be scheduled in terms of switching on/off. For instance, in Figure 2, the controller checks the distribution of vehicles in each RSU. Then, vehicles within the RSU-3 can be assigned to a new RSU according to their positions. Here, the power levels of vehicles are estimated to connect a particular RSU and then RSU-3 is switched off. The modules are explained in the next subsections.

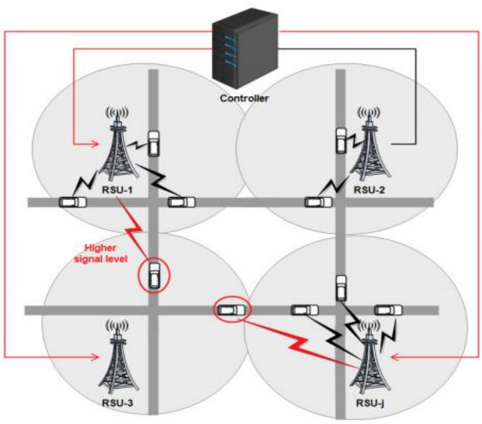


Figure 2. The proposed model development.

2.1. Applying ArcGIS

ArcGIS (Geographic Information System (GIS)) [6] is an application which is used to create maps, manage the geographic data and perform spatial analysis. In this paper, ArcMap, which is one of the main components of ArcGIS, is used. It creates maps, performs spatial analysis, manage geographic data and share results in both 2D and 3D environment.

Spatial analysis tool is used to analyze geographic data in ArcMap. The used geographic data and spatial analysis tool will be explained in the next subsection.

2.2.1. Kriging

Ordinary Kriging module [7] is used in ArcMap as a spatial analysis to estimate the vehicle's power level at the position (t, x_0, y_0) at time t, so that vehicles are assigned to a new RSU as seen in the Figure 2.

Kriging is an interpolation method to predict a variable at an unknown position from the observed values at nearby locations in geostatistics. In Kriging, the variation and distance between known data points are weighted according to spatial covariance. Then, unknown value is estimated by using the obtained weights that are based on the surrounding data points. The covariances and weights are determined according to network topology and distance between vehicles.

Ordinary Kriging is chosen for model development. Ordinary Kriging predicts weighted linear combinations of measured data while minimizing variance of the errors. It uses semivariogram analysis to define spatial correlation of two sample positions; it does not depend on their absolute position but only on their relative position.

It is assumed that there are N vehicle locations $(x_i, y_i; i = 1,...,N)$ in the communication range of a RSU. In addition, signal level is initially known and, demonstrated as $Z(t, x_i, y_i)$ at the location (x_i, y_i). With the help of this information, each vehicle is assigned to one RSU.

To keep the estimate unbiased, it is important to define the weights of nearby vehicles within the communication range of one RSU. Then, optimal signal level can be estimated. In Ordinary Kriging, the weighted linear estimator for location $Z(t, x_0, y_0)$ is expressed in Equation 1.

$$Z^*(t, x_0, y_0) = \sum_{i=1}^{N} w_i Z(t, x_i, y_i) \tag{1}$$

where $Z^*(t, x_0, y_0)$ represents power level at location (x_0, y_0). Weight, w_i, is a coefficient.

The weights are calculated to minimize error variance. It is implemented by solving the following equation for the Kriging weights.

$$\gamma(h_{i,j}) w_i = \overline{\gamma}(h_{i,0}) \tag{2}$$

Here, $\overline{\gamma}(h_{i,0})$ provides a weighted scheme. When the covariance between data samples and the position being detected enhances, the accuracy of the estimation will increase so that nearest samples have significant weights and the covariance between near points will increase.

To solve the weights, Equation 2 is multiplied on both sides by γ^{-1} so that Equation 3 is given as follows:

$$\begin{aligned} \gamma(h_{i,j}) w_i &= \overline{\gamma}(h_{i,0}) \\ w_i &= \gamma^{-1}(h_{i,j}) \overline{\gamma}(h_{i,0}) \end{aligned} \tag{3}$$

where γ represents semivariogram and is a function based on the distance between vehicles. It is determined in Equation 4.

$$\begin{aligned} \gamma(h_{i,j}) &= \gamma(x_i y_i - x_j y_j) \\ &= \frac{1}{2} E[(Z^0(t, x_i, y_i) - Z^0(t, x_j, y_j))^2] \end{aligned} \tag{4}$$

Exponential model in Ordinary Kriging is used for the analysis as given in the following equation. The reason to choose this model can be explained as follows: The main characterizations of ITS are the mobility of vehicles and vehicle directions. In this method, we observe that the covariance between

RSUs and vehicles depends on the distance between them and Kriging makes the calculations according to these distances.

$$\gamma^{\exp}(h_{i,j}) = C_0 + C_1(1 - \exp(\frac{-3h_{i,j}}{a}) \tag{5}$$

where C_0 represents nugget effect, that enables discontinuity at the origin. Semivariogram value at the origin is 0 in theory. The value of "a" represents the range that is a covariance value as constant and longest distance between RSU and vehicle.

The spatially estimated power of the vehicle at (x_0, y_0) is given as follows:

$$Z^{\exp}(t, x_0, y_0) = \sum_{i=1}^{N} w_i^{\exp} Z^0(t, x_i, y_i) \quad \forall i \in N \tag{6}$$

Figure 3 shows the obtained exponential semivariogram model. In the figure, an estimation process can be observed. Here, it is checked whether a vehicle can be connected to a new assigned RSU depending on the distance between vehicles and RSUs.

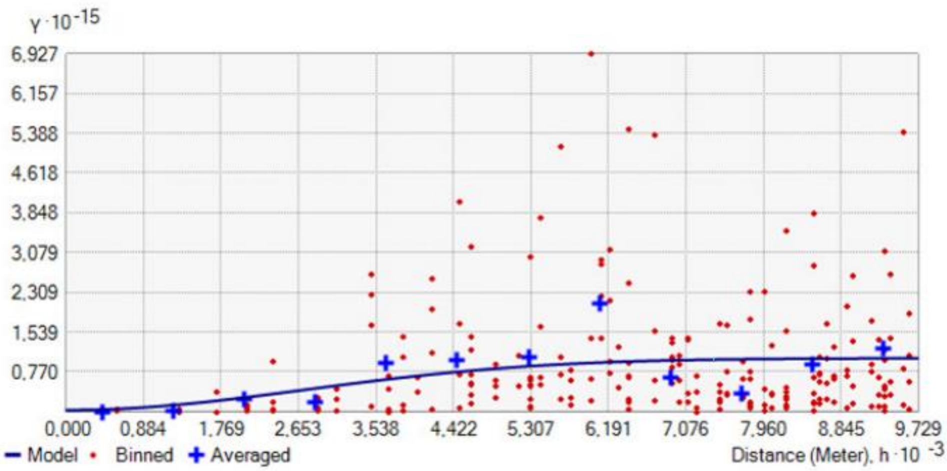


Figure 3. The Semivariogram Model.

Figure 4 shows an example of the power estimation process for a vehicle to connect a new assigned RSU. Here, one of the challenges is the limitation for power. The maximum power limit is 33 dBm for non-government services in ITS and 44.8 dBm for government services. Therefore, each estimation is checked after the proposed model run and the maximum limitation is assigned as 33 dBm.

In Kriging, when the covariance between each of sample point increases, the accuracy of the estimation will improve. This means that when the data points are closer to each other, then nearest samples carry significant weight so that error variance is minimized and optimal and unbiased estimates are obtained. Semivariogram calculates the distance between all vehicle pairs within the range of a RSU and this information provides the clustering of the available sample data in the topology. Here, clustering is done with the help of semivariogram. Therefore, Ordinary Kriging estimates the unknown values based on distance and clustering.

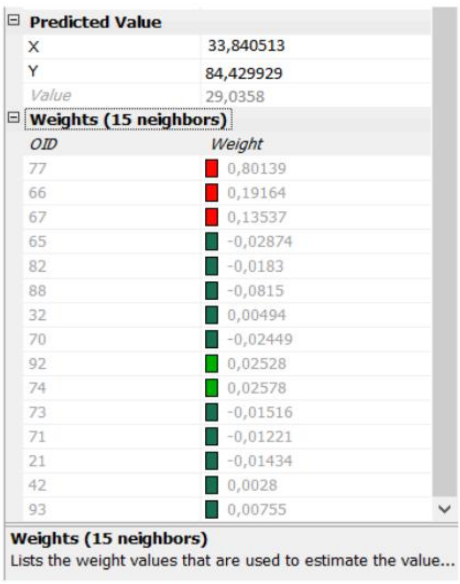


Figure 4. Estimation process.

3. DATA AND METHODOLOGY

In order to observe vehicles' movement, traces of real vehicle from the King County, Washington obtained from CRAWDAD (A Community Resource for Archiving Wireless Data at Dartmouth) [8] are used. This dataset contains the measurement of the performance of short range communications between vehicles. It is contributed by R. M. Fujimoto, R. Guensler, M. P. Hunter, H. Wu, M. Palekar, J. Lee, J. Ko.

The used data for the simulation includes the time, vehicle latitude and longitude, direction, speed and signal strength (dBm). Some modifications are done over the original data. As a modification, power strength is adjusted 23 dBm at initial situation for all vehicles. Then, the power level is calibrated with the spatial interpolation method.

For the experiments, a subset of these traces covers 27Kmx47Km of area and movements from different time periods. Figure 5 shows the density map of the studied area.

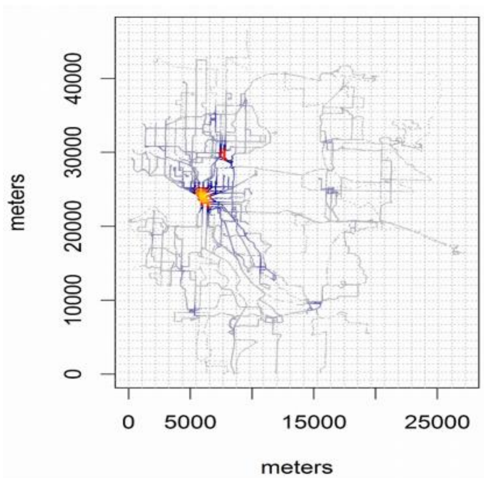


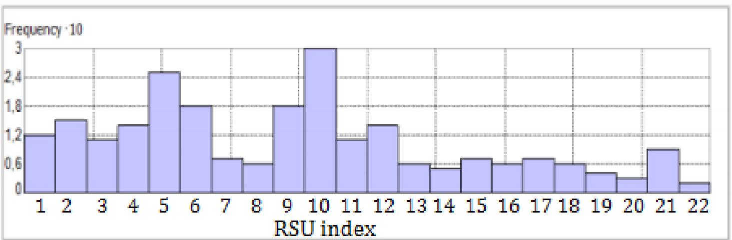
Figure 5. Density map of the area in study.

4. MODEL PREDICTIONS AND RESULTS

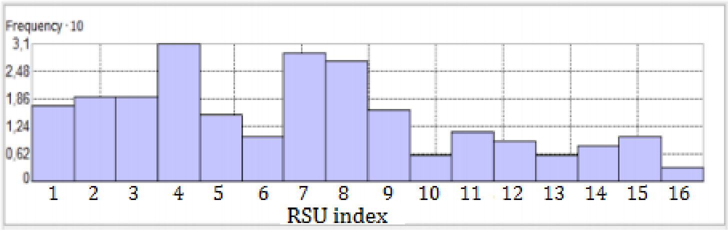
In this section, the proposed energy management model is evaluated in ITS. Exponential scheme in Ordinary Kriging is used to predict vehicles' signal level. The controller schedules to RSUs to decrease energy consumption of RSUs.

It is assumed that RSUs are deployed along the road with a full coverage of the environment with mean inter-RSU distance of 300m as defined in IEEE 802.11p. At initial, vehicles have allocated 23dBm to connect to the RSUs. Depending on the distribution of vehicles, 3 traffic densities are considered: low traffic, medium traffic and high traffic. Traffic density is defined by the number of vehicles per square kilometer. 760, 1140 and, 1920 vehicles are simulated for the traffic densities, respectively.

Figure 6 shows the density of vehicles in each RSU in low traffic density. Here, total number of RSUs is equal to 22. At initial situation, each RSU serves the vehicles within the communication range of itself. The density of vehicles is showed in Figure 6(a). On the other hand, after the proposed model is applied, RSUs are scheduled and 6 RSUs are switched off. Figure 6(b) illustrates the distribution of each RSU after the proposed energy management model is implemented.



(a)



(b)

Figure 6. The density of vehicles within RSUs (a) Initial situation (b) After the proposed model.

Moreover, Figure 7 demonstrates the energy efficiency over the simulation time for each traffic density. When the traffic density is low and medium, energy efficiency is achieved 29% and 18% with the proposed energy management model, respectively. However, it is observed that when the traffic density increases, energy efficiency cannot be achieved as seen in the Figure 7. Here, all RSUs need to be active for a full coverage of the environment depending on the distribution of vehicles in each RSU. However, it is clear that the model effectively decides the minimal number of RSU to serve all vehicles in the environment and enables energy efficiency.

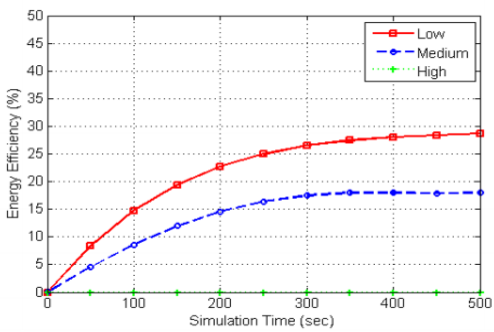


Figure 7. Energy efficiency for different traffic densities.

5. CONCLUSION

In this paper, an energy management model is proposed for ITS to schedule RSUs and thereby decrease the energy consumption. At first, the optimal signal level of vehicles is estimated with the help of ArcGIS so that vehicles connect to new assigned RSUs. Then RSUs are scheduled depending on the distribution of vehicles and as many as possible RSUs are switched off to decrease energy consumption in ITS. The ongoing work involves the effect of the connectivity algorithms among vehicles and between vehicles to RSUs.

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