2015

Traffic Signal Battery Backup Systems Use of Event-Based Traffic Controller Logs in Performance-Based Investment Programming

Mo Zhao
Iowa State University, mozhao@iastate.edu

Anuj Sharma
Iowa State University, anujs@iastate.edu

Edward Smaglik
Northern Arizona University

See next page for additional authors

Traffic Signal Battery Backup Systems Use of Event-Based Traffic Controller Logs in Performance-Based Investment Programming

Abstract
A stable supply of power is critical element for reliable traffic signal operation. Battery backup systems are often used to prevent traffic signals from power disruption. Currently, battery backup systems are designed using engineering judgment due to a lack of operational requirements and well-defined performance measures. New high resolution traffic controllers now have the ability to record event based data for power failures and traffic counts at a tenth of a second resolution. Equipped with this high-resolution data, the paper proposes a performance-based investment programming using average annual signal downtime (AASD) over the analysis period as a performance measure. AASD is stochastically estimated using hazard-based duration models developed with power failure data. A volume and functional class weighted stochastic optimization scheme is then presented for a battery backup system project planning by sizing battery capacity to minimize AASD for a network under given budget constraints.

Keywords
traffic signals, uninterruptable power supply, backup power, average annual signal down time, investment programming, battery backup, power failure models

Disciplines
Civil and Environmental Engineering | Transportation Engineering

Comments
This is a manuscript of an article from *Transportation Research Record* 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

Authors
Mo Zhao, Anuj Sharma, Edward Smaglik, and Tim Overman

TRB 15-4415: Performance-based Investment Programming for Traffic Signal Battery Backup Systems Using Event Based Traffic Controller Logs

Mo Zhao
Department of Civil, Construction and Environmental Engineering
Iowa State University
2711 S Loop Dr. Suite 4700
Ames, Iowa 50010-8664
Email: mozhao@iastate.edu
Phone: 402-730-0741

Anuj Sharma
Department of Civil, Construction and Environmental Engineering
Iowa State University
Email: anujs@iastate.edu
Phone: 515-294-3624

Edward Smaglik, Ph.D., P.E.
Department of Civil Engineering, Construction Management, and Environmental Engineering
Northern Arizona University
Bldg 69, Rm. 122N
Flagstaff, AZ 86011
Email: edward.smaglik@nau.edu
Phone: 928-523-1431

Tim Overman
Indiana Department of Transportation
Traffic Control Systems
Email: toverman@indot.in.gov
Phone: 317-690-6632

Word count = 6,179

Figures and Tables = (4) ×250= 1,000

Total = 7,179

Submission date: March 15, 2015

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

ABSTRACT

A stable supply of power is critical element for reliable traffic signal operation. Battery backup systems are often used to prevent traffic signals from power disruption. Currently, battery backup systems are designed using engineering judgment due to a lack of operational requirements and well-defined performance measures. New high resolution traffic controllers now have the ability to record event based data for power failures and traffic counts at a tenth of a second resolution. Equipped with this high-resolution data, the paper proposes a performance-based investment programming using average annual signal downtime (AASD) over the analysis period as a performance measure. AASD is stochastically estimated using hazard-based duration models developed with power failure data. A volume and functional class weighted stochastic optimization scheme is then presented for a battery backup system project planning by sizing battery capacity to minimize AASD for a network under given budget constraints.

Keywords: traffic signals, uninterruptable power supply, backup power, average annual signal down time, investment programming, battery backup, power failure models.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

INTRODUCTION

Battery Backup Systems (BBS) for traffic signals have been widely used at signalized intersections in the U.S. to ensure uninterrupted traffic signal operation. Typically, traffic signal operating agencies use a standard design specification for all BBS implementations. For example, the Texas Department of Transportation requires that all the uninterruptable power supply (UPS) systems in its jurisdiction should be able to power an LED-only intersection at full operation (typical load of 700 watts) for four hours, and then revert to flashing operation (350 watt load) for additional two hours when 40% of battery charge is remaining (*1*). The California Department of Transportation requires the BBS to have enough capacity to supply power for full operation of LED signals lights for at least two hours (*2*). Currently, typical transportation agency practices for BBS investment lack a systematic approach to quantify the impact and requirements of BBS and aid in performance-based investment decisions. After an exhaustive literature review, it was found that commonly available BBS configuration strategies were simplistic and deployment strategies for BBS were rarely available. No performance metric was available in the literature that quantified the impact of BBS on traffic signal power reliability. The BBS project development is not a formalized one with performance-based criteria connecting projects to the goals of traffic signal operation. The simplistic rule of thumb design strategy is often used due to lack of good data and well-defined performance measures, and thus, a BBS might be over-designed at intersections with less power supply issues and a lower power load. Conversely, the battery size deployed may not be sufficient for intersections with long and frequent power failures.

To implement a site-appropriate BBS, it is necessary to study the traffic signal power load profile and power failure history, and design the system based on power demand. According to the guidelines for traffic signal energy back-up systems developed for New York State (*3*), data on power outage records can greatly benefit the BBS investment programming. The new high resolution traffic controllers now have the ability to record event based data for signal power failures and traffic counts at a tenth of a second resolution (*4*). These high resolution data make it possible to develop performance measures for efficient BBS investment programming. This ties BBS implementation into performance-based planning as it is emerging trend in transportation investment programming, aiding in decisions about using limited funds to meet needs (*5*).

This paper studies traffic signal system reliability using high resolution traffic signal controller data in terms of adequacy of power supply and develops a performance-based BBS investment programming model. Probabilistic models are developed to assess the Annual Average Signal Downtime (AASD) with a log-logistic hazard model used for the power failure duration, and a kernel-based non-parametric hazard model is used for the duration of time-to-failure. s. A volume and road functional class weighted investment programming strategy is then presented, and stochastic optimization tools are used in the presented strategy to design BBS capacity that achieves a maximum power reliability under given budget constraints. A case study is conducted to illustrate the practical application of the method.

TRAFFIC SIGNAL POWER RELIABILITY

Definition of Traffic Signal Power Reliability Metric

According to the definition by the IEEE reliability is the ability of a system or component to perform its required functions under stated conditions for a specified period of time (*6*). This

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

paper extends the definition of power reliability to be used as a performance metric of traffic signal systems. It aims to evaluate traffic signal system reliability in terms of adequacy of power supply.

The Traffic Signal Downtime (TSDT), is defined as the time when a signal system fails to perform its intended function in a specified analysis period due to lack of power supply, and is represented by notation "U_d". If the traffic signal can be automatically restored to the intended operation immediately after power is restored, the downtime (U_d) equals to the duration of the power failure (D). In other cases where the traffic signal needs to be reinitialized to revert to the intended operation, the downtime (U_d) would be the duration of power failure (D) plus the technical response time to reset the signals. AASD, or Average Annual Signal Downtime, is the annual signal downtime averaged over the analysis period.

TSDT Modeling

The subsequent sections present statistical models developed for traffic signal power failures. The models are developed using high resolution signal controller logs collected from 136 signalized intersections in Indiana from April 1, 2012 to April 13, 2014. The high resolution traffic controller logs included intersection name, time of power outage occurred, and time of power restored. In the studied two years, only seven of these 136 intersections had no power failures. There was an average of four failures at each intersection. The intersection with the highest failure rate had 20 failures.

Failure Duration Distribution

A power outage may last several hours, a few minutes, or even just an instant. Usually, power outages of less than five minutes are considered momentary. Power can be restored within moments, but momentary outages may cause power surges that can damage traffic signal equipment. Power outages that last more than five minutes are considered sustained. Sustained outages can cause significant impact (*7*).

Hazard-Based Duration Model Hazard-based duration models have their origin in biometrics and industrial engineering, and have been widely used in reliability and economic analyses (*8*). Hazard-based duration models have been used to model the duration data encountered in transportation field, such as highway incident duration, shopping activity duration for trip generation, and the time until a vehicle crash occurs (*9*, *10*, *11*). A hazard-based duration model is used to study the conditional probability of a time duration ending at some time t, given that the duration continues until time t (*12*). The cumulative distribution function, $F(t)$, is in the following format:

$$F(t) = P\ (T < t) \qquad (1)$$

In this equation, P is the probability, T is a random time variable, and t is some specified time. For example, consider the duration of a power outage as beginning when the outage occurs. Equation 1 gives the probability of having a power outage end before time t. The density function of this distribution is

$$f(t) = dF(t)/dt \qquad (2)$$

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

with the corresponding hazard function as:

$$h(t) = f(t)/[1 - F(t)] \qquad (3)$$

The hazard function, *h* (*t*), is the conditional probability that an event will occur between time *t* and *t* + *dt*, given that the event has not occurred up to time *t*.
The survivor function, *S* (*t*), is also frequently used in hazard-based duration models. *S* (*t*) is the probability that a duration is greater than or equal to some specified time, *t*. The function is:

$$S(t) = P(T \geq t) = 1 - F(t) \qquad (4)$$

One important specification in modeling duration data with hazard-based duration models are the distributional assumptions of the baseline hazard, as the baseline hazard distribution can be either parametric or nonparametric. A number of distributions have been used for fully parametric hazard models, including exponential, Weibull, log-logistic, gamma, and Gompertz. In general, there is little theoretical support for the selection of any particular parametric distribution (*9*), and the choice of baseline hazard distribution among parametric and nonparametric distribution is noted as complicated (*12*). Parametric models are appropriate when the underlying distribution of duration is known or theoretically justified, whereas nonparametric models are more suitable for a situation where the underlying distribution of duration is not known (*13*).

There are some distributions used with regularity in reliability analysis, such as the Weibull and log-logistic distributions. Usually, the choice of distribution is made by considering one of the following characteristics (*9*, *12*, *14*):

- The theoretical properties of the distribution are consistent with the analysis conditions and the physics of the studied event.
- The probability density adequately describes the studied event history.

Selection of Baseline Hazard Distribution In this study, hazard-based duration models are developed for both the duration of traffic signal power failures and the duration of time between successive failures. Individual intersections are assumed to be independent when studying power failures. The duration of traffic signal power failures is rarely studied in literature, and there is a lack of a theory that would recommend a specific baseline hazard distributional assumptions. Therefore, several distributions were tested including exponential, Weibull, gamma, log-normal, and log-logistic distributions.

Field Data Analysis At the 136 studied intersections, the longest observed power outage lasted more than 28 hours, but most outages were less than 2 hours. The distributions discussed above were fitted to these field data. The exponential, Weibull, gamma, log-normal, and log-logistic distributions were evaluated for the best fit using maximum likelihood estimates (*12*). Likelihood ratio tests (*12*) were conducted to compare the fitness of these distributions. The test statistic of the likelihood ratio test is χ^2 distributed with degree of freedom of one. Comparing Weibull distribution to exponential distribution resulted in a test statistic of -22.57, which indicates that the Weibull model is not superior to the exponential model at 95% confidence level. The test statistic for comparing gamma distribution to exponential distribution is -11.75, and the null hypothesis that the gamma model is superior to the exponential model was rejected

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

at 95% confidence level. The exponential distribution with a simpler density function than the other two was considered.

Log-normal and log-logistic distributions were also explored. The fit of log-logistic model had a much higher value of log-likelihood. Compared to the log-normal distribution, the log-logistic distribution is preferable for hazard-based duration model as it has a closed form for the hazard and survivor functions (*12*).

The fitted log-logistic and exponential distributions are compared in in Figure 1, plotted along with a histogram of the field power outage duration data. The formula for the exponential probability density function is

$$f(t) = \lambda e^{-\lambda t} \qquad (5)$$

With $\lambda > 0$, the hazard function is

$$h(t) = \lambda \qquad (6)$$

The hazard function is constant for the exponential distribution implying no duration dependence. In other words, for exponential distribution the probability of power being restored at any given time t is independent of duration of power failure. Thus the conditional probability of a power failure ending in a specific time interval is the same regardless the length of the interval.

The probability distribution function of log-logistic distribution with parameters greater than zero is

$$f(t) = \lambda P(\lambda t)^{P-1}[1 + (\lambda t)^P]^{-2} \qquad (7)$$

with corresponding hazard function being

$$h(t) = \lambda P(\lambda t)^{P-1}[1 + (\lambda t)^P]^{-1} \qquad (8)$$

In this equation, λ is the scale parameter and P is the shape parameter.

To compare log-logistic and exponential distributions as the distributional assumption for a hazard-based model for signal power failure duration, the followings steps were performed:

(1) χ^2 tests to test the fit of the assumed distributions to the field data,
(2) A consistency check with the underlying physics of traffic signal power failures.

For the log-logistic distribution, the null and alternative hypotheses of the χ^2 test are:

H_0: The duration data come from a log-logistic distribution with parameters estimated from that data

H_a: The duration data are not from a log-logistic distribution

The results of this analysis showed that the null hypothesis was accepted at the 95% confidence level with a p value of 0.718. For the exponential distributions, the null hypothesis, that the

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

duration data comes from an exponential distribution with a parameter estimated from the data, was rejected at the at the 95% confidence level with a p value of 0.014 Thus the log-logistic model has a better fit to the field data as compared to the exponential model.

In addition, the exponential model has a constant hazard rate and the probability of a duration ending is independent of time. The constant hazard rate is not consistent with the characteristics of power outage duration, as the power can be restored (the failure duration ends) quickly after a momentary power outage, but it usually takes some time to restore the power after a sustained outage. Therefore, the log-logistic distribution was made as distributional assumption of the hazard-based model for studying the traffic signal power failures. The hazard function and survivor function of the log-logistic model are shown in Figure 2.

The mathematical characteristics of hazard function provide important insights to the underlying behavior of power failures observed at studied traffic intersections. The slope of the hazard function in Figure 2 captures the dependence of the probability of a power outage ending at the length of the outage duration. The hazard increases in duration from zero to an inflection point, $t = (P-1)^{1/P}/\lambda \approx 26$ minutes, and decreases towards zero thereafter. This implies that for power outage durations of less than 26 minutes, the hazard function is monotonically increasing, indicating that the probability of the outages ending soon was increasing. This reflects the facts at the studied sites that grid power was easy to be restored from short outages. Usually, the electrical grid can reset automatically to recover from momentary power outages. For outage durations greater than 26 minutes, the hazard function is monotonically decreasing in duration, meaning the longer the power outages last, the less likely it is that it will end soon. This is consistent with the fact that more time and effort is needed to recover from sustained outages, especially for cascading blackouts. The survival probability is decreasing in duration, implying that longer power outages have a lower likelihood of occurrence.

Time to Failure Distribution

To fully characterize traffic signal power failures, information on both failure duration and frequency are necessary. The time elapsed between power outages can be used to calculate the frequency of power outages in a given time period. Here, the time elapsed from when traffic signal power is restored to the time when the next power outage occurs is defined as Time to Failure (TTF). Some distributions are frequently used in reliability analyses for modeling TTF, such as exponential, Weibull, and lognormal distributions (*14*). These distributions were fitted to the field data using maximum likelihood estimate for estimating parameters. However, all these fully parametric distributions failed the χ^2 tests at 95% level of significance. As there was not enough evidence to justify any of the parametric distributional assumptions, a nonparametric hazard model was developed.

The nonparametric approach can model duration data without relying on specific or well-behaved statistical distributions (*12*). A nonparametric density estimation, kernel density estimation, is used to estimate the parameters of the non-parametric hazard model. A kernel is a non-negative function that integrates to one. The kernel is placed on each data point to make a smooth estimate of the probability density function. Assuming that $(t_1, t_2, \ldots, t_n)$ are independent and identically distributed samples from an unknown distribution with a probability density function *f*, the kernel density estimator is

$$\widehat{f_h}(t) = \frac{1}{n}\sum_{i=1}^{n} K_h(t - t_i) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{t - t_i}{h}) \quad (9)$$

In this equation, h is the bandwidth and acts as a positive smoothing parameter and K is the kernel that is a symmetric function which integrates to one upon application of the equation. The normal, triangular, box, and Epanechnikov distributions are commonly used as kernel functions, however the result of kernel density estimate often do not change significantly with different kernel functions(*15*). The estimated nonparametric models with different kernel function are shown in Figure 3. The normal kernel was selected for the hazard model as it efficiently produced good estimates in that the function was decreasing in duration and approaching zero when the TTF duration was large. The decreasing hazard indicates the longer the traffic signals operate without having a power failure, the less likely they are going to have one soon. This correlates with the field data.

Reliability Measure

The power outage and TTF duration models developed in the previous section can now be used to stochastically estimate the TSDT. The TSDT duration is not always equal to the duration of power outage. If the traffic signals cannot be restored to normal operation immediately after the power is restored, it takes some time for the maintenance crew to reach the site and reinitialize the signals. A variable, ΔD, is introduced to represent the time needed to dispatch a maintenance crew and re-initialize the traffic signals. Then, the downtime ($U_{d,i}$) during the ith power failure in an analysis period T can be estimated as:

$$U_{d,i} = D_i + \Delta D_i \quad (10)$$

D_i is the duration of the i^{th} power failure in the analysis period (T). Assuming ΔD was half hour, the average TSDT at each of the 136 studied intersections was about 3 hours per year. The results indicate a relatively stable supply of power at the studied intersections. All of the studied intersections are located in areas with a well-developed electrical grids.

Simulation of Power Failure History

The proposed BBS sizing design explicitly accounts for the stochastic nature of signal power failures by using Monte Carlo Simulation (MCS). MCS is a random sampling method developed based on the principles of using frequency to approximate probability. MCS randomly samples from probability distributions for each input. MCS can simulate the random effects and provide stochastic estimates of reliability of a system (*16*). In this study, MCS is used to predict power system state (up or down) sequence for the analysis period.

MCS samples each input variable for each time step from its probability distribution and predicts the value of the variable. The process repeats until a pre-defined stop criterion is met. The stop criterion can be the maximum number of iterations or the tolerance error. The input variables to MCS include traffic signal power load, power failure rate (transition rate from up state to down state) and the transition rate from system down state to up state, with transition rates used to model the duration and frequency of system states (*17*). The MCS uses a uniform random variable to determine the probability of staying in the current system state, and an inverse transform method is used to determine the duration of current state (*18*). Then, the

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

duration of the next system state is calculated in similar manner and added to the total simulation time. This process is repeated until the defined simulation time is reached and there are a sufficient number of samples. The following steps are included in the MCS:

1) Assuming the power system is just restored from a failure, the simulation starts with an up state at time T_0. The simulation time is updated such that $T_s = T_0$.

2) Generate a uniformly distributed random number X between [0, 1].

3) The transition rate from the present state to the next state at time t is $h = h(t)$, with $h(t)$. When the system transits from up state to down state (TTF to failure), h is the above developed hazard model of TTF at time t. When the system transits from a failure state to an up state (failure to TTF), h is the above developed hazard model of power failure at time t.

4) Assuming the duration of the present system state follows the distribution $h(t)$, the cumulative distribution of this probability density function, $H(t)$, is the cumulative hazard distribution in the hazard-based duration model. The probability of staying in the present state is $S = S(t) = 1 - H(t)$, with $S(t)$ as the survivor function. If $S(t) = X$, then the time t can be obtained from the inverse transform, $t = S^{-1}(X)$.

5) Record the duration data. If the present state is in failure state, update the total number of failure states. The simulation time is then updated to $T_s = T_s + t$.

6) Check the stop criterion. If the stop criterion is reached (the objective simulation time is reached and the maximum iteration is reached, or the coefficient of variation of the cumulative frequency is less than the tolerance error), stop. If not, repeat the procedures starting at step 2) to generate the next power system state.

PROBLEM FORMULATION AND SOLUTION METHODOLOGY

Now that the models have been developed and presented, the overall problem can be addressed, that of investment programming for proper BBS capacity, the objective of which is to find the optimal capacity BBS that minimizes the TSDT within a limited budget. The significant aspect of the proposed method is volume and functional class weighted and reliability-based sizing instead of a uniform capacity for all intersections. The reliability measure is integrated into the model as an inequality constraint.

Estimation of AASD

The AASD for a signalized intersection, without BBS, is estimated using the simulated power failure data from MCS. The AASD estimates for various BBS sizes are then generated using the following approach. The BBS is assumed to be in full charge state at the beginning of the analysis period. During the i^{th} power failure of duration D_i , the energy consumed from battery system, $B_{con,i}$, is:

$$B_{con,i} = \min\{Ca \cdot DOD, E_{D,i}\} \qquad (11)$$

where Ca is the capacity of BBS (kWh), DOD is the depth of discharge of the battery, and $E_{D,i}$ is the total energy demand during a power failure. It equals the production of traffic signal power load (L_i) and the duration of power failure:

$$E_{D,i} = D_i \cdot L_i \qquad (12)$$

Then, the time needed for the battery to reach full charge after the i^{th} power failure is:

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

$$T_{c,i} = \frac{B_{con,i}\left(1 + \frac{B_L}{100}\right)}{Vol} / I_B \quad (13)$$

where, I_B is the current of the battery charger, B_L is the energy loss during battery charging, and Vol is the BBS system voltage. At the time when the $(i+1)^{th}$ power failure occurs, the available energy stored in battery (B_a) would be:

$$B_{a,i+1} = \begin{cases} Ca, & U_{up,i+1} \geq T_{c,i} \\ Ca - \left(1 - \frac{U_{up,i+1}}{T_{c,i}}\right) B_{con,i}, & others \end{cases} \quad (14)$$

The total backup energy (E_{back}) for the $(i+1)^{th}$ power failure equals to the energy stored in the battery, that is:

$$E_{back,i+1} = B_{a,i+1} \quad (15)$$

With this amount of backup energy, the duration of the $(i+1)^{th}$ power failure becomes:

$$D'_{dn,i+1} = \max\{0, \quad [D_i - \frac{E_{back,i+1}}{L_{i+1}}]\} \quad (16)$$

Then, the signal system downtime during the $(i+1)^{th}$ power failure is:

$$U'_{dn,i+1} = D'_{dn,i+1} + \Delta D \quad (17)$$

Here, ΔD is the time needed for the traffic signals to revert to the intended operation after power is restored. Then, the AASD (U_{DA}) can be estimated as:

$$U_{DA} = \frac{\sum_i^N U'_{dn,i}}{Y} \quad (18)$$

Here, N is the total number of power failures in the analysis period of Y years.

Establishing Relative Importance Weights

In network level BBS programming, it is necessary to explicitly or implicitly assign relative weight to each intersection to reflect its importance compared to the others. For example, to what extent is the reliability improvement at one intersection more important than that at other intersections? Equal weighting can be used for a simple analysis. In this paper, a two-step direct weighting approach is used (*19*). This weighing method assigns relative importance weights by road functional classification and Average Daily Traffic (ADT). The ADT are computed using the event logs generated by high resolution traffic signal controllers. The intersections are first classified into category by the function of major approach, and assigned a weight among categories. A weight of 1 is assigned to a reference category, and the weights of other categories are assigned in proportion to their importance compared to the reference category. For example, if the urban minor arterial is used as a reference category, the urban principal arterial might be assigned a weigh greater than 1. If the major and minor approaches are both in important functional class, both approaches can be assigned a weight and the intersection category weight might be calculated by multiply these two weights. In the second step, the traffic volume is used to assign weights within each category. According to the *Traffic Signal Manual of Texas*

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

Department of Transportation, the BBS is most beneficial at intersections with total volume of all approaches in excess of 20,000 ADT (*20*). Using 20,000 ADT as a reference volume with weigh 1, each intersection is assigned a weight in proportion to its ADT compared to the reference ADT. The weight for each intersection (w) can be estimated by

$$w = w_1 \times w_2 \tag{19}$$

where, w_1 is the weight among categories and w_2 is the weight within a category.

Investment Programming Problem Formulation

The problem formulation considers the scenarios from the planning perspective. This scenario has a given budget (B_u) for a one-time initial investment. The objective is to maximize the signal network reliability, that is, minimize the overall average annual downtime (U'_{aM}), which is a weighted sum of the individual AASD ($U'_{a,m}$) of the M intersections in the network. The input variables are randomly sampled from their probability distribution, therefore, it is not possible to express the objective function with fixed independent variables. An implicit function including the variables and parameters is used to represent the objective function with the optimization problem presented as:

$$\text{Min } U'_{aM} = \sum_{m=1}^{M} w_m \times U'_{a,m} \quad \left(Ca_m, h_d, h_{ttf}, L_m, C_{Ib}\right) \tag{20}$$

Subject to: $\sum_{m=1}^{M} C_{a,m} \times C_{Ib} \leq B_u$

$Ca_m \leq B_m$

Here, w_m is the weight for intersection m, Ca_m is the capacity of BBS at intersection m (kWh), h_d and h_{ttf} are the hazard functions for power failure duration and TTF duration, respectively. L_m is the traffic signal power load, C_{Ib} is the installed cost of BBS (\$/kWh), and B_m is the BBS capacity limit. The first constraint is the budget constraint, and the second is the battery capacity limit due to space constraints at an intersection.

Solution Methodology

A Genetic Algorithm (GA) is used to find the capacities that minimizes the objective functions. GA is developed based on the mechanism of natural selection. The individuals in the population compete with each other and the stronger individual survives. Each individual has a chromosome consisting of genes that represent an individual characteristic (*21*). GA is stochastic and has a good chance of searching the entire design space; therefore, it has a very high likelihood of identifying a globally optimal solution (*22*).

GA was used in this research to find the battery configurations satisfying the optimization criteria. The MCS generates traffic signal power failure estimates including durations of each power failure and TTF in the analysis period. These data are used as input parameters for the optimization model. GA initializes the decision variables, that is, the BBS capacity at each intersection, and then checks the constraints and calculates the objective function using Equation 10 to 18 and Equation 20. Stop criteria, maximum iterations or a minimum difference in values of objective function, are set to check if the optimal solution is found. If the stop criteria are not met, GA would adjust the decision variables and repeat the process until the optimum is found.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

CASE STUDY

To illustrate the methodology presented, a case study has been undertaken, the details of which are described in the succeeding sections.

Assumptions

This case study aims to demonstrate the proposed method with a BBS sizing design for 18 intersections in Indiana using the logs from the high resolution traffic controllers. These intersections are in the same district of the INDOT jurisdiction as shown in Figure 4 with an identity number (ID) for each intersection.

Listed below are some important characteristics of the studied system.

• Power load per signal	700 watt
• BBS voltage	24 V
• DOD of batteries	80 %
• Loss of energy while charging batteries	40%
• Current of Battery charger	15 Amp
• Installed cost of battery	$ 500 / kWh
• Fixed cost for other equipment such as UPS/cabinet to house batteries	$ 3000 /BBS

The empirical distributions of power failure duration and TTF duration developed with field data are used as distributional assumptions for the hazard-based duration models with a tolerance error of 0.05 used as the stop criterion of MCS. The time needed to reinitialize traffic signal after power failure, ΔD, is assumed to be thirty minutes. In a typical case when a BBS of fixed capacity is used, the batteries should have a capacity of at least 2.8 kWh to maintain full signal operation for four hours. It would cost $79, 200 to install such a BBS at each of the intersections.

Modeling Results

The objective is to design BBS capacities that minimize the overall weighted AASD with a one-time investment. From the MCS, the AASD at each intersection is about 10 hours. To establish the relative importance weights, the roadways are classified into five functional classes based on INDOT classification: interstate, other freeway and express way, other principal arterial, minor arterial, major collector, and minor collector (*23*). The reference functional class, other principal arterial, is assigned a weight of 1. The weights of other classes are defined by an increment or decrement of 0.2 according to their rank compared to the reference class.

Intersections 6 and 7 on the ramps of interstate are assigned a category weight of 1.4, and all other intersections on roadways in other principal arterial class are assigned a category weigh of 1.The weights within each functional class are assigned based on total ADT of all approaches with weight 1 for 20,000 ADT. The ADT for each intersection is also shown in Figure 4. The weighted AASD at each intersection is about 33 hours.

With an investment of $80,000, all the 18 intersection can achieve uninterrupted full signal operation (zero downtime).The total BBS installed cost is about $76,695. Compared to installing a 2.8 kWh BBS at each intersection, the optimization solution provides high reliability at lower cost. If this level of performance is not desired, the weighted AASD per intersection could be 3.6 hours with $60,000 budget and 8.3 hours with $40,000 budget. The weighted AASD

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

with BBS installation for each intersection in these two budget conditions are also reported in Figure 4.

To design the BBS capacity while minimizing the weighted AASD, GA is used to solve the optimization problem under budgets constraints of $80,000, $60,000 and $40,000, respectively. The determined BBS capacities in these budget conditions are shown in Figure 4.b. The AASD increases with the decreasing of budget. When budget was not sufficient, GA preferred the intersections with high relative importance weights. Intersections 6and 7 are assigned high weights because they are located on the ramps of interstate highways that intersect with other principal arterials, and the ADT is also high. Intersections 2, 5, 10, 12, 14, 15 and 18 have higher weight because of the higher ADT than the others. These intersections were given enough BBS capacity to obtain zero downtime in all three budget conditions. The results seem supportive of the thought that higher relative importance weights lead to higher priority in BBS capacity selection, hence ensuring higher reliability. For intersections with similar weight, the optimization prefers the most cost-effective design that minimized the objective function. By changing the weight scheme, it is possible to integrate user-specific criteria into the analysis, such as intersection geometry, safety measure, and signal repair response time into the optimization model. The results also indicates that the weight assignments impact project fund allocation and therefore weight establishment is an important part of the programming analysis.

CONCLUSION

This paper develops a methodology to assist BBS investment by sizing the capacity of a BBS by considering both traffic signal operation and budget requirements. The hazard-based duration models are developed to aid in evaluating the potential benefit of BBS, and in optimizing the BBS investment by understanding the attributes of traffic signal power failures. An analysis comparing the volume and functional class weighted AASD at different intersections could help to select BBS installation locations and determine the installation priority. This performance-based method would increase the efficiency of BBS project planning and help to guide the investment toward the regional goals and objective of traffic operation.

While this paper developed a stochastic method for investment programming of BBS for traffic signals, the method shown can be used for BBS project planning for other ITS applications without the loss of generality, including network level planning or individual project development. The method combines MCS and GA to take into account of the stochastic characteristics of input variables. Use of this method could help transportation agencies make more informed decision on BBS investment.

Lastly, it should be noted that this research focuses on the operational reliability of traffic signals only in terms of average signal downtime. The effects of traffic signal equipment failures are not considered, but they can be added within the model framework if sufficient field data are available to establish appropriate models for these equipment failures. Both this area and that discussed in the preceding paragraph would be a good area for future work in this venue.

References

1. *Uninterruptible Power Supply (UPS) System for Signal Cabinets*. Texas Department of Transportation Special Specification TO-8248. Texas Department of Transportation, 2009. http://ftp.dot.state.tx.us/pub/txdot-info/gsd/pdf/to8248.pdf. Accessed June 5, 2014.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

2. Specifications for Battery Back-Up System. State Of California Department Of Transportation, 2009. http://www.dot.ca.gov/hq/traffops/tech/tees-docs/BBS_July_2009.pdf. Accessed July 5, 2014.
3. Wallace, W. A., J. Wojtowicz, D., Torrey, N., Renna, and J. *Tan. Guidelines for traffic signal energy back-up systems*. Technical Report No: 09-05. Center for Infrastructure and Transportation Studies, Rensselaer Polytechnic Institute, 2009.
4. Smaglik, E. J., A. Sharma, D. Bullock, J. Sturdevant, and G.Duncan. Event Based Data Collection for Generating Actuated Controller Performance Measures. *Transportation Research Record*, no. 2035, Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 97-106.
5. *Transportation Project Prioritization and Performance-based Planning Efforts in Rural and Small Metropolitan Regions*. NADO Research Foundation. September 2011.
6. IEEE. IEEE Standard Computer Dictionary: A Compilation of IEEE Standard Computer Glossaries. New York, NY, 1990.
7. Outage Causes. DTE Energy. https://www2.dteenergy.com/wps/portal/dte/business/problemsSafety/details. Accessed June 5, 2014.
8. Hensher, D. A. and F. L. Mannering. Hazard-based Duration Models and Their Application to Transport Analysis, *Transport Reviews*, 14, 1, 1994, pp. 63-82.
9. Bhat, Chandra R. A Hazard-Based Duration Model of Shopping Activity with Nonparametric Baseline Specification and Nonparametric Control for Unobserved Heterogeneity. *Transportation Research Part B*, Vol. 30, No. 3. 1996, pp. 189-207.
10. Kim, Soon-Gwan and Fred L. Mannering. Panel Data and Activity Duration Models: Econometric Alternatives and Applications. Panels for Transportation Planning Transportation Research, Economics and Policy 1997, pp 349-373.
11. Nam, D., and F. Mannering. An exploratory hazard-based analysis of highway incident duration. *Transportation Research Part A*, 34, 2000, pp. 85-102
12. Washington, S. P., M. G. Karlaftis, and F. L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis*, *Second Edition*. Chapman& Hall/CRC Press, Boca Raton, FL, 2010.
13. Lee, E. *Statistical Methods for Survival Data Analysis*, *Second Edition*. John Wiley & Sons, Inc., New York, 1992.
14. Bendell, A., M. Walley, D. W. Wightman, and L. M. Wood. Proportional hazards modelling in reliability analysis—an application to brake discs on high speed trains. *Quality and Reliability Engineering International*, vol 2, issue 1, 1986, pp. 45–52.
15. Silverman, Bernard W. *Density Estimation for Statistics and Data Analysis.* Chapman and Hall, London, 1986.
16. Hu, Huafen. Risk-Conscious Design of Off-Grid Solar Energy Houses (Doctoral dissertation). Georgia Institute of Technology, 2009.
17. Billinton, R and A. Sankarakrishnan. System state transition sampling technique for reliability evaluation. *Reliability Engineering & System Safety*, Volume 44, Issue 2, 1994, pp 131–134.
18. Billinton, R. and W. Li. Reliability assessment of electric power systems using Monte Carlo methods. Plenum Press, New York, 1994.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

19. *Multi-Criteria Analysis: A Manual*. Department for Communities and Local Government, London, 2009.
20. *Traffic Signals Manual*. Texas Department of Transportation, 2011. http://onlinemanuals.txdot.gov/txdotmanuals/tff/tff.pdf. Accessed May 5, 2014.
21. Goldberg, D. E. *Genetic Algorithm in Search, Optimization, and Machine Learning*. Addison-Wesley, Boston, MA, 1989.
22. Khosravi, A., B. Mazloumi, S. Nahavandi, D. Creighton, J. W. C. Van Lint. A genetic algorithm-based method for improving quality of travel time prediction intervals. *Transportation Research Part C*, 19 (6), 2011, pp.1364–1376.
23. INDOT Roadway Inventory. https://gis.in.gov/apps/DOT/RoadwayInventory/. Accessed July 5, 2014.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

List of Figures

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

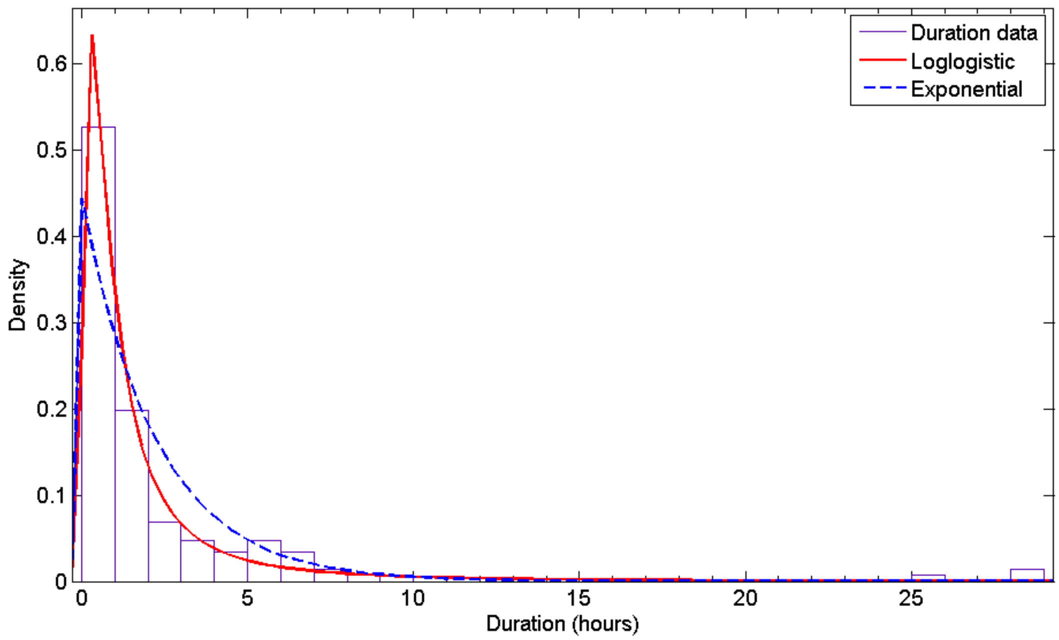


FIGURE 5 Duration data and fitted exponential and log-logistic models.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

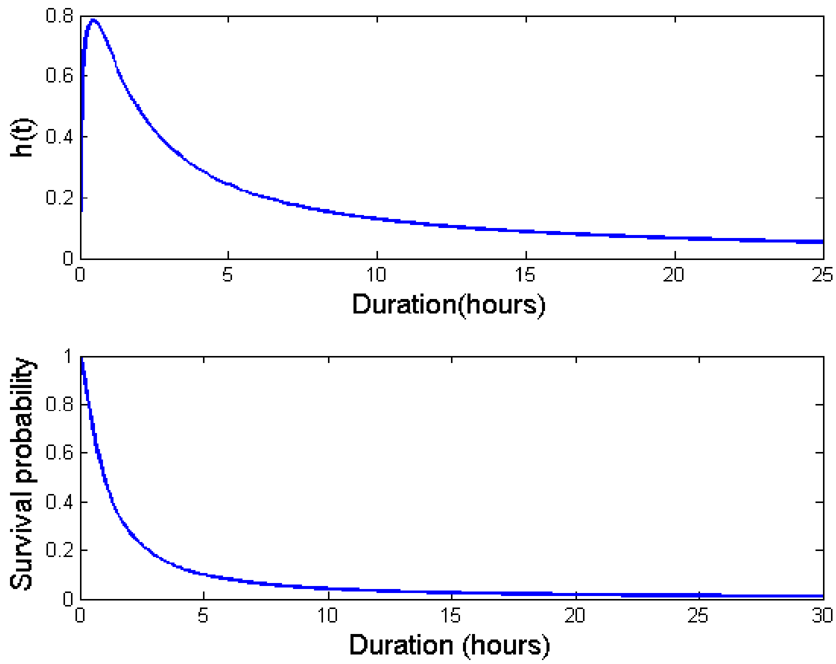


FIGURE 6 Estimated hazard and survivor functions for the log-logistic model.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.

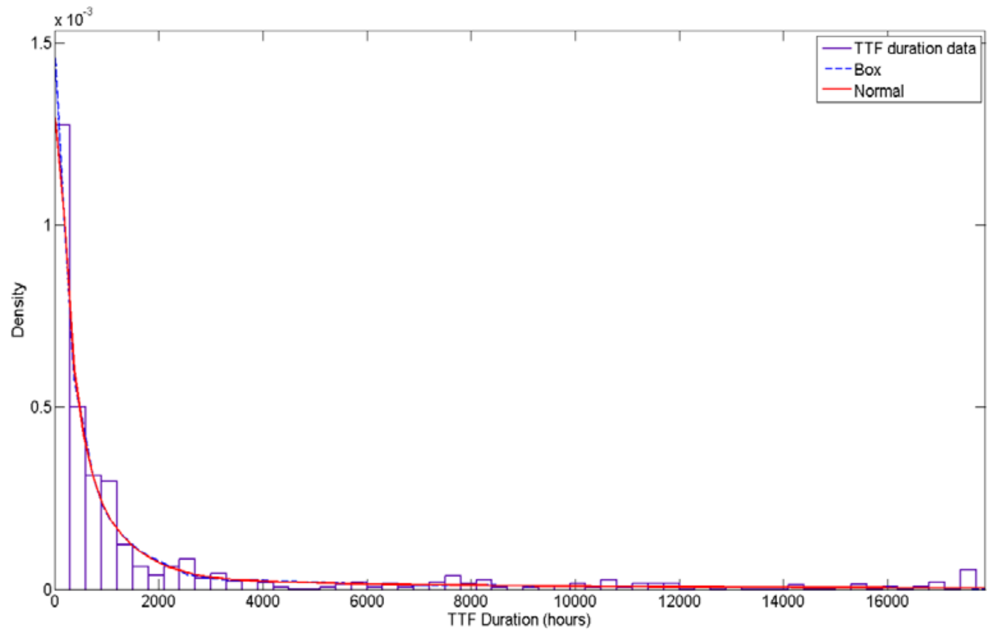
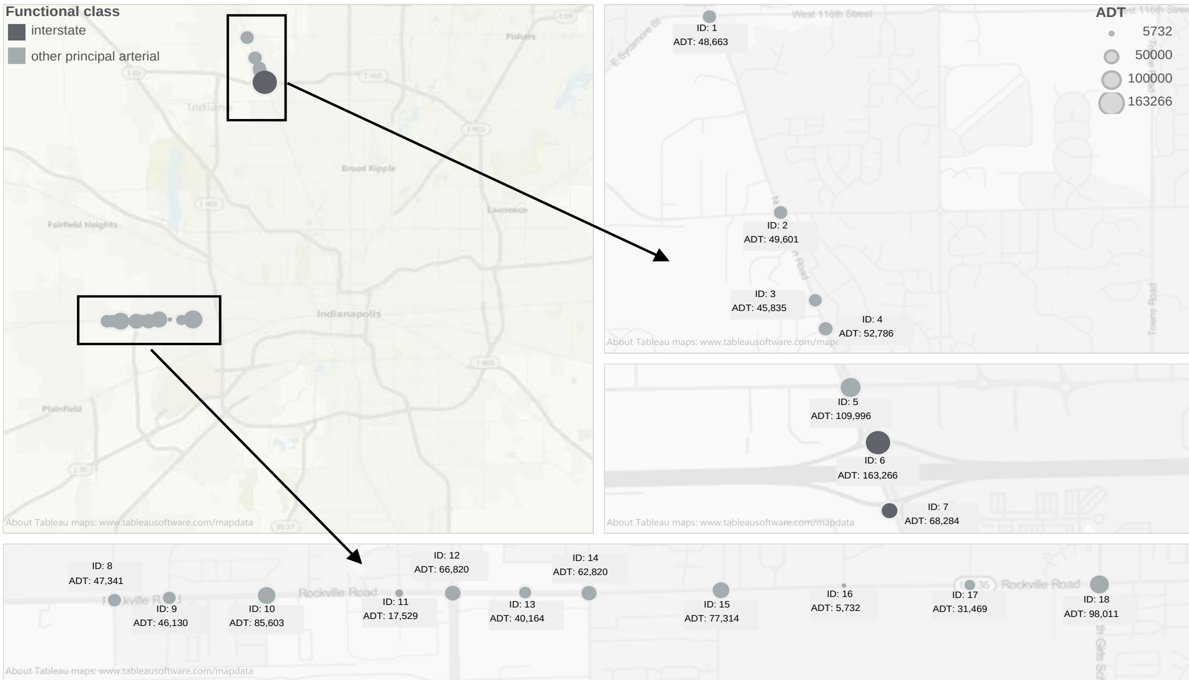
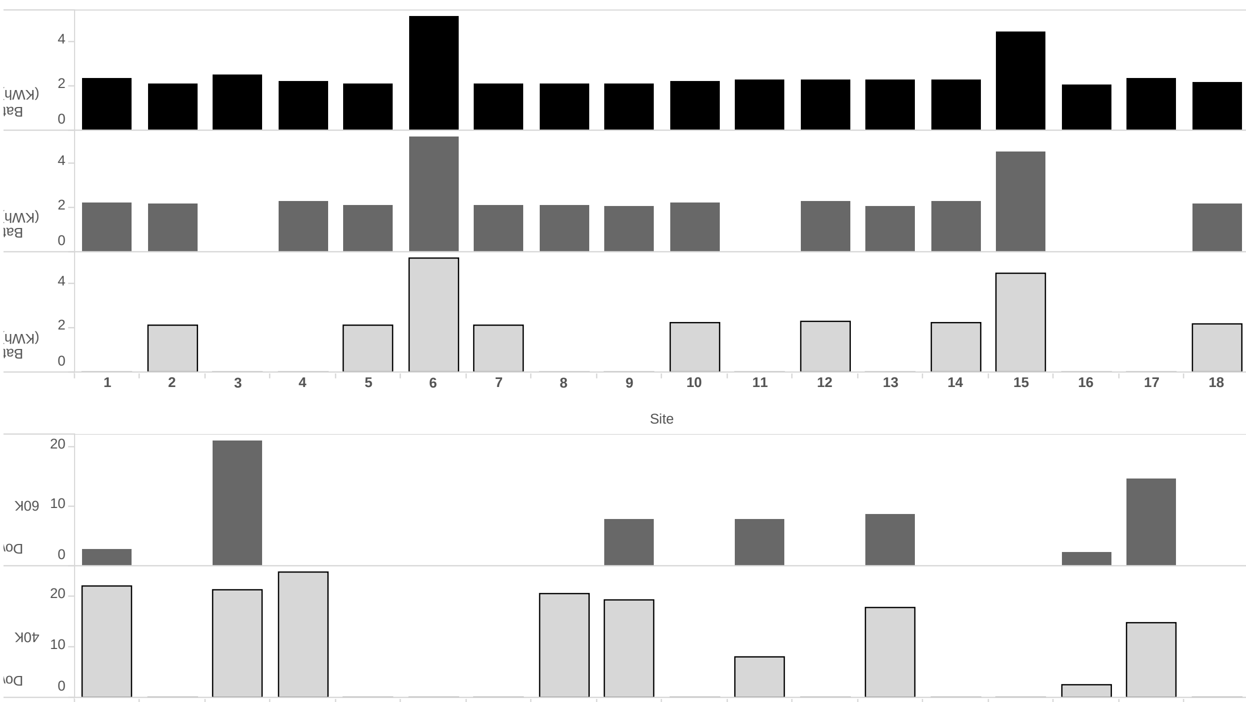


FIGURE 7 TTF duration data and estimated nonparametric models.

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.



a.



b.

FIGURE 8 Case Study Sites and BBS Capacities in Indian

This is a manuscript of an article from Transportation Research Record 2488 (2015): 53, doi: 10.3141/2488-06. Posted with permission.