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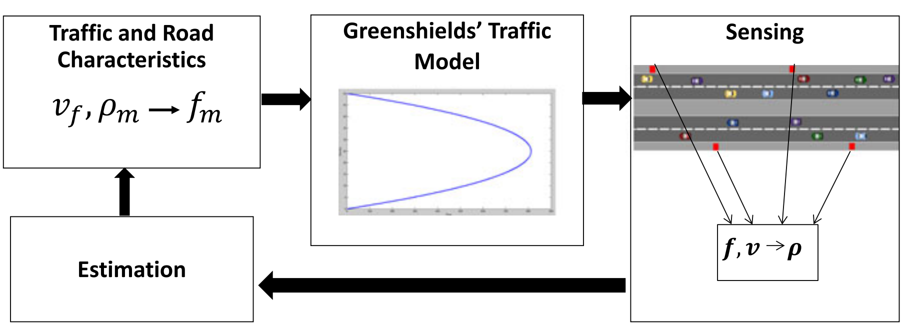

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A Novel Illuminance Control Strategy for Roadway Lighting Based on Greenshields Macroscopic Traffic Model

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Abstract: Most street lights currently deployed have constant illumination levels or vary based on a predetermined schedule. However, with advances in lighting controls, intelligent transportation systems, and the efforts of transportation agencies at regional and national levels to better sustain and manage the transportation system by monitoring the roadway network, many different types of real-time traffic data are available; which enables the implementation of a traffic responsive outdoor light system. The International Commission on Illumination (CIE) has proposed a class-based lighting control model based on a number of roadway parameters, some of which are traffic related. However, the adaptation of the available traffic data to the existing model is not obvious. In addition, the CIE model can be improved to better reflect traffic characteristics to increase energy efficiency of the overall street lighting system. The intention of this research is to quantify the relationship between real-time traffic, and roadway lighting and to develop a control strategy based on real-time traffic data in order to reduce light energy consumption, enhance safety, and maximize throughput of the roadway. Significant energy savings were observed when the proposed control strategy was implemented in two case studies using available lighting and traffic data for Washington, DC, and Montgomery County, MD, representing urban and rural roadway networks, respectively.

Index Terms: Roadway lighting, light-emitting diode (LEDs), illuminance control.

1. Introduction

Roadway lighting plays a vital role in the functioning of the transportation system specifically in terms of safety and throughput. However, the benefits of brighter roads come at a high price of energy inefficiency and light pollution. The United States uses an estimated 52.8 TWh of electric energy annually [1]. Globally, roadway lighting is believed to account for 159 TWh of electricity use per year [2], which is responsible for the consumption of approximately 20% of the world's electric energy [3], [4]. Several technologies have been introduced to reduce the energy consumption of the overall streetlight system.

Sun *et al.* propose an adaptive light-emitting diode (LED) luminaire that delivers a roadway-shape light pattern in order to maximize illumination performance by efficiently and homogeneously directing luminaire where needed [5]. Mahoor *et al.* employ a Brute-Force search algorithm to minimize a group of street lighting poles in order to reduce energy consumption [6]. This system describes an overall control architecture for a more efficient outdoor lighting system; however, the dimming aspect is schedule based and can be enhanced by an adaptive control strategy with real-time parameter estimation as proposed in this paper.

LED-based streetlights are expected to provide significant energy savings. However, the introduction of LED streetlights is only a first step, as energy consumption can be further reduced by deploying intelligent controls. For instance, dimming the light level at certain parts of the network that are at low vehicle and pedestrian traffic demand can optimize energy savings while meeting standard safety regulations.

In reviewing the state-of-the-art of street-lighting technology, it is noted that although all lighting market segments are adopting solid state lighting, by far the leading segment adopting solid state lighting is street lighting. Yet, the vast majority of street lights today are based on inefficient light sources, such as sodium vapor and metal halide. In addition to LEDs, the lighting industry is introducing other new technologies at a rapid pace as well, such as adaptive controls and connectivity to offer comprehensive solutions for operation and management of outdoor lighting. Advanced control systems combine controls and connectivity to enable remote operation, configuration and monitoring of outdoor lighting assets over large areas. Advancements in localization and extraction of light poles is also vital to be able to quantify performance [7]. An overview of recent developments in this space is presented in Cavalcanti *et al.* [8].

Despite these advances in the outdoor lighting industry, traffic responsive outdoor lighting is not widely deployed today, due to limitations in standards and uncertainty in regulations leading to concerns (e.g., liability) from system operators, authorities and citizens. In addition, the benefits of traffic responsive lighting have not been previously quantified.

The first steps towards traffic responsive outdoor lighting are seen in schedule-based and sensor-based lighting control systems. It is inevitable that significant inefficiencies are inherent in the schedule based system. This becomes clear if one considers the two scenarios. In the first scenario, a certain illumination level is outputted in areas that have no or very low traffic density and the system can afford to be dimmed; however, since it is schedule-based, it cannot adapt to the actual environmental parameters. Therefore, energy efficiency is compromised. In the second scenario, the illumination level can be scheduled to be low at certain hours given the assumption that very low traffic density is present; however, if an incident occurs during these hours, then unexpected traffic behavior is typically observed. In this case, the schedule based light control does not have the ability to respond autonomously to such unexpected conditions, leading to compromised safety.

The widespread availability of sensors and communication technologies has been utilized by some to integrate traffic data with lighting controls in certain applications; however, significant gaps remain in determining the implication of measured traffic data to lighting control on the roadway environment. This study considers the various parameters that are used to macroscopically model and characterize traffic based on Greenshields model [9] enhancing the International Commission on Illumination's (CIE) recommended illumination level model and control strategy. Two case studies for Washington DC and Montgomery County, MD, representing urban and rural roadway networks respectively, are conducted to demonstrate the benefits of the proposed adaptive control scheme methodology.

2. CIE Recommendation Model and Illuminance Level Control Strategy

The International Commission on Illumination (CIE) has published a technical report containing recommendations on illuminance levels based on various roadway parameters, namely, CIE 115:2010, titled: Lighting of roads for motor and pedestrian traffic [10]. The purpose of this recommendation is to improve the performance of the luminaires and enhance energy efficiency through adaptive lighting. The U.S. Department of Transportation recently also published "Guidelines for The Implementation of Reduced Lighting on Roadways" [11], whose dimming model is very similar to the one in CIE 115:2010. Therefore, the CIE recommendation model was considered in this paper. It is important to recall that in practice, advanced control systems have not yet reached mainstream

TABLE 1
Parameters for Lighting Class Selection in the CIE Model

Parameter	Range	Description
Speed: V_v	$\{0, 0.5, 1\}$	Moderate, High, Very High
Traffic Flow: V_f	$\{-1, -0.5, 0, 0.5, 1\}$	Very Low-Very High
Traffic Composition: V_c	$\{0, 1, 2\}$	Motorized-Highly Mixed
Separation of Carriageways: V_s	$\{0, 1\}$	Yes, No
Intersection Density: V_d	$\{0, 1\}$	Moderate-High
Parked Vehicles: V_p	$\{0, 0.5\}$	No, Yes
Ambient Luminance: V_L	$\{-1, 0, 1\}$	Low-High
Visual Guidance/Traffic Control: V_T	$\{0, 0.5\}$	Good-Poor

TABLE 2
Class and Corresponding Average Luminance, Illuminance

Class	M1	M2	M3	M4	M5	M6
Avg. Illuminance (lx)	50	30	20	15	10	7.5

adoption, and most advanced systems for roadways and streets currently deployed use schedule based lighting control.

2.1 The CIE Model

According to the CIE 115:2010 adaptive lighting model, the average luminance or illuminance for a given road segment can be adapted to traffic flow and composition, weather conditions, and ambient luminance. The eight different roadway parameters used in the model are given as discrete values and correspond to predefined descriptions as shown in Table 1.

Traffic characteristics such as speed and flow, traffic composition, roadway characteristics, and environmental factors are considered in the CIE model. These parameters are assigned weighing values based on their description and the actual conditions. The determined values for each parameter are then summed resulting in the weighing value V_{ws} given in (1).

$$V_{ws} = V_v + V_f + V_c + V_s + V_d + V_p + V_L + V_T \tag{1}$$

After the weighing factor is determined, the class of illumination is determined based on (2) which gives rise to six different classes.

$$M = \lfloor 6 - V_{ws} \rfloor \tag{2}$$

The correspondence between the class and the illuminance level as per CIE 115:2010 is given in Table 2. These values assume road surface photometric characteristics at average luminance coefficient of $q_0 = 0.05\, cd \cdot m^{-2} \cdot lx^{-1}$.

2.2 Limitations of the CIE Model

The CIE model takes into account several key roadway parameters in order to determine the appropriate illuminance level. It is expected that following this model will result in much more energy efficient and safer roadway lighting.

TABLE 3
Modified Continuous Weighing Values for Model Parameters

Parameter	Range	Description
Speed: V_v	[0, 1]	Moderate, High, Very High
Traffic Flow: V_f	[−1, 1]	Very Low-Very High
Traffic Composition: V_c	0, 2	Motorized-Highly Mixed
Separation of Carriageways: V_s	0, 1	Yes, No
Intersection Density: V_d	[0, 1]	Moderate-High
Parked Vehicles: V_p	0, 0.5	No, Yes
Ambient Luminance: V_L	[−1, 1]	Low-High
Visual Guidance/Traffic Control: V_T	[0, 0.5]	Good-Poor

Potential enhancement to the existing model resides in determining the weighing value of the flow. The CIE definition for the flow parameter requires assigning a low weighing value to (Table 1) when flow is low, resulting in a higher lighting class M (2), which in turn results in low illuminance level. On the other hand, a high weighing value corresponds to high flow levels corresponding to a low lighting class and therefore to a high illuminance level. The context of the CIE documentation indicates that high flow corresponds to high density traffic levels whereas low flow indicates low traffic density level. This statement, however, is inaccurate since flow does not linearly depend on traffic density. For instance, low flow can result from very few vehicles in the system or a congested system, and the appropriate lighting strategy for the two situations is different. Additionally, since the model takes only discrete values, it is evident that there is further potential for enhancement by creating a continuous model which automatically improves energy efficiency.

The remainder of this paper proposes and evaluates an enhanced lighting control model in order to overcome the limitations of the current model.

3. Proposed Lighting Level Modeling and Control

The original CIE model is transformed to have continuous dependency on its parameters. Then the weighing value of the flow is corrected to reflect the appropriate traffic density level. Estimation models for the necessary parameters are developed and are directly represented as measured values. This model calls for real time system level implementation.

3.1 Continuous Dependency on Roadway Parameters

As mentioned earlier, the model's enhancement of continuous dependency on roadway parameters results in a more energy efficient and safer system. Similar to the CIE model, Table 3 lists the definitions of the system's model parameters and their corresponding new continuous weighing value ranges guaranteeing that the extreme values or boundaries are maintained at the same level as in the original CIE model. Note that the roadway parameters for "separation of carriageways" and presence of "parked vehicles" remain discrete, whereas, all the other parameters are continuous.

As in the original CIE model, the values determined for each parameter are then summed resulting in the weighing value V_{ws} given in (3).

$$V_{ws} = \sum \left(V_v, V_f, V_c, V_s, V_\rho, V_p, V_L, V_T\right) \tag{3}$$

After the weighing factor is determined, the class of illumination is determined based on (4).

$$M = 6 - V_{ws} \tag{4}$$

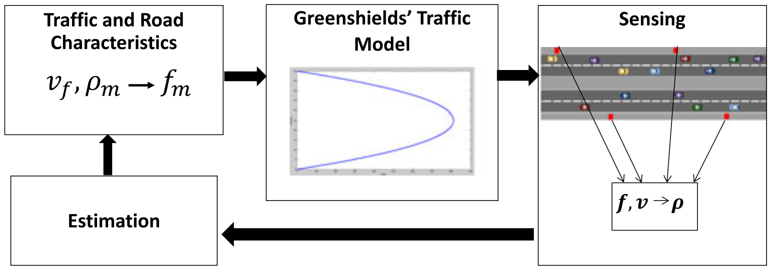

Fig. 1. Traffic modeling and parameter estimation process.

However, the goal now is to have continuous correspondence to the illuminance level within the recommended range of [50*lx*, 7.5*lx*]. This can be obtained by using (5).

$$E = \left(1 - \frac{M-1}{5.88}\right) 50 \tag{5}$$

where [$E \in 7.5lx, 50lx$] is the illuminance level in *lx*. The direct relation is obtained by substituting (4) in (5) and is given in (6).

$$E = \left(1 - \frac{5 - (V_v + V_f + \sum(V_c, V_s, V_\rho, V_p, V_L, V_T))}{5.88}\right) 50 \tag{6}$$

Note that roadway parameters related to traffic, namely speed and flow (weighing values $V_v \& V_f$), are dynamic parameters, whereas, the remaining are static. Both static and dynamic parameters have an impact the chosen light levels.

3.2 Understanding Traffic Characteristics

Now that illuminance, E, is a direct function of weighing values of traffic condition, it is also desired to have a direct relationship between these values and traffic conditions. Several aspects are involved in order to accomplish this step of deriving the traffic parameters based on traffic conditions. First, one must understand what the empirical traffic flow characteristics are, how to model traffic flow using the determined characteristics, how to sense these parameters based on measurements, and how to properly estimate those parameters from measurements. As the block diagram in Fig. 1 suggests, Greenshields traffic model is used to describe macroscopic traffic flow characteristics emphasizing the relationship between traffic speed and density under the presence of two main parameters, maximum speed and jam density. These parameters are influenced directly by roadway and environmental characteristics, for example street capacity, weather conditions, and speed limit, and must be estimated from sensor data. The sensed data usually contains counts and speed, from which density can be obtained. Collecting data over a wide range of time and traffic conditions allows as to perform estimation in order to obtain the free-flow velocity v_f and jam density ρ_m.

3.2.1 Modeling: There are mainly three parameters that describe traffic flow parameters macroscopically, (v_f) free-flow speed, (ρ_m) jam density, and (f_m) maximum flow, as shown in the traffic and road characteristics block in Fig. 1. Researchers have proposed many models that describe traffic behavior and the relationship between flux and traffic conditions. Greenshields model, given in (7) (and shown in Fig. 1), is one of the most used.

$$f(t) = v_f \rho(t) \left(1 - \frac{\rho(t)}{\rho_m}\right) \tag{7}$$

where $f(t)$ is the flux or traffic flow as a function of time and $\rho(t)$ is the traffic density (the rest of the parameters are defined earlier). Equation (7) is derived from (8) which describes the relationship between speed, v, density, ρ, and flow, f.

$$f = \rho v \tag{8}$$

3.2.2 Estimation of Traffic Parameters: Free-flow speed, v_f, and jam density, ρ_m, reflect traffic flow characteristics and are to be estimated from data. For most roads, temporal and spatial traffic flow and speed data are available from sensors and can be used for the parameter estimation by using (7) which can be rewritten as

$$f(t) = v_f \rho(t) - \frac{v_f}{\rho_m}\rho(t)^2 \tag{9}$$

This can be written in a matrix form as shown in (10) which can be linearized by setting the variables to be ρ and ρ^2 and the coefficients to be v_f and $\frac{v_f}{\rho_m}$ as shown in the equality statements given in 11 and 12, respectively.

$$f = W\beta \tag{10}$$

where,

$$W = \begin{bmatrix} w_1 & w_2 \end{bmatrix} = \begin{bmatrix} \rho & -\rho^2 \end{bmatrix}, and \tag{11}$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} v_f \\ \frac{v_f}{\rho_m} \end{bmatrix} \tag{12}$$

Based on continuous measurement of speed and vehicle count, the Jam density can be estimated. Since the equation is written in a linear manner, the best bulk estimate of β can be obtained in the L^2 sense. Applying least squares, we have,

$$\hat{\beta} = [W'W]^{-1}W'y \tag{13}$$

β can also be estimated iteratively for real time operations as follows,

$$\hat{\beta}_{k+1} = \hat{\beta}_k + [W'W]^{-1}W'(y - W\hat{\beta}_k). \tag{14}$$

3.2.3 Real-time Light Level Control with Parameter Tuning: As discussed previously, both static and dynamic roadway parameters determine light levels. Dynamic roadway parameters are traffic based, namely those related to speed and flow ($V_v \& V_f$). These are computed as follows:

$$V_v = \frac{v}{v_f} \tag{15}$$

$$V_f = sgn\left(-\frac{df}{d\rho}\right)\frac{f}{f_{\max}} = sgn\left(\frac{2\rho}{\rho_m} - 1\right)\frac{4f}{v_f\rho_m} \tag{16}$$

$$V_\rho = \frac{\rho}{\rho_m} \tag{17}$$

where, $V_v \in [0, 1]$, $V_f \in [-1, 1]$, $\& V_\rho \in [0, 1]$.

The relationship between density and flow can be seen in Fig. 2. E is given by the following.

$$\begin{aligned} E &= \left(1 - \frac{5 - (V_v + V_f + V_\rho + \sum V_{static})}{6}\right)50 \\ &= \left(1 - \frac{5 - (\frac{v}{v_f} + sgn\left(\frac{2\rho}{\rho_m} - 1\right)\frac{4f}{v_f\rho_m} + \frac{\rho}{\rho_m} + \sum V_{static})}{6}\right)50 \end{aligned} \tag{18}$$

The static parameters (V_c, V_s, V_p, V_L, V_T) must be carefully chosen for each case study, as these parameters also impact light levels. For instance, consider the influence of ambient light on light level control. In urban areas, the ambient light levels are high. Therefore, the CIE model requires that street lights be set brighter. Similarly, in the presence of parked vehicles on the street, the CIE model requires higher lux levels.

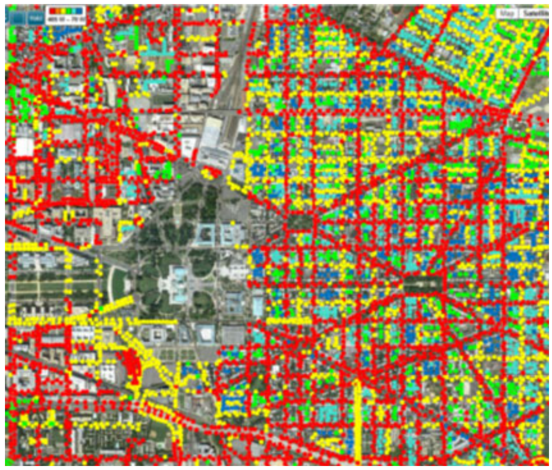

Fig. 2. Map data for Washington DC with an overlay of light pole data.

3.2.4 Illuminance Quantification: In order to calculate the electric power P expended to achieve a certain amount of lighting at street level, a simplified approach was used. Given that,

$$\phi_v = P\eta \tag{19}$$

where,
ϕ_v Luminous Flux, $[lm]$
P Total electric Power, $[W]$
η Luminous Source Efficacy, $[lm/W]^*$
and that $\theta = 45^\circ$, we have $a = h^2$

$$E_v \approx \frac{\phi}{h^2} = P\frac{\eta}{h^2} \tag{20}$$

where,
$E_v \in [7.5lx, 50lx]$
$P \in [0, P_{\max}]$

4. Case Studies

Two case studies were conducted, Washington DC and Montgomery County MD, representing urban and rural roadway networks, respectively, where data related to street lights and real-time traffic was obtained as elaborated in the next few sections.

4.1 Light Pole Data

Data related to light poles for both Washington DC, Fig. 2 and Montgomery County MD locations were gathered. In the District of Columbia, there are 64,940 light poles, whereas, in Montgomery County MD, there are 27,468 light poles. For both locations, for each light pole, information such as light pole height, light source type, rated power, longitude, and latitude were gathered. Light source type included high pressure sodium, incandescent, mercury vapor and metal halide and are indicated by the red, green, yellow, and blue dots, respectively, in Fig. 2. The efficiency of each light source used in this case study is provided in Table 4.

4.2 Google Traffic Data

Next data related to traffic was gathered, utilizing publicly accessible data from Google maps. The Google maps application provides typical traffic data based on historical measurements of

TABLE 4
Efficiency of Light Sources Used in Case Studies

Light Source	η [lm/W]
High Pressure Sodium	85–150
Incandescent	5–20
Mercury Vapor	25–60
Metal Halide	65–115

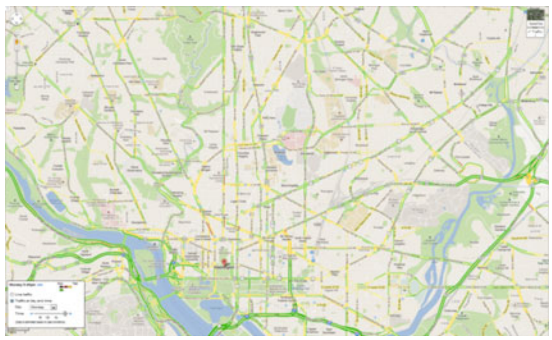

Fig. 3. Google maps image showing traffic data for Washington DC.

TABLE 5
Google Maps Data Format Used for Parameter Estimation

Speed v	Flow veh/15min	Flow f veh/hr	Density ρ veh/mile	ρ^2

traffic for the two chosen locations as shown in Fig. 3. Furthermore, the traffic data is provided at the fine granularity of 15-minute resolution for any given weekday. The purpose of the historical data is to plan and predict the duration of drive taking into account the cyclical nature of traffic (depending upon the time of the day and day of the week). Nonetheless, we found this data to be extremely useful in estimating the average (or typical) traffic in the chosen locations for our case study.

To obtain this data, images from Google maps were captured. Simple image processing software was developed to extract traffic conditions on roadways based on color (e.g., red for congestion, green for flowing traffic)These locations (latitude, longitude) were stored for further processing. The final data format obtained is depicted in Table 5.

Based on traffic conditions, the sum of dynamic parameters was later derived and combined with sum of static parameters and used to calculate light levels, E, as discussed previously.

4.3 Static Roadway Parameters

In addition to the traffic conditions which determine dynamic parameters, several static roadway parameters also influence light levels in both the CIE model and the proposed approach. These static parameters include traffic composition (cars only or mixed), separation of carriageways, intersection density, whether there are parked vehicles on the side of the roadway, the ambient luminance and finally, if the street lighting is providing the function of visual guidance about the

TABLE 6
Roadway Parameter Values Used for Static Parameters for Washington DC and Montgomery County MD Use Cases

Parameter	Value Range	Description	DC	MD
c	$V_c\{0, 1, 2\}$	Motorized-Highly Mixed	1	0
s	$V_s\{0, 1\}$	Yes, No	0	1
ρ	$V_\rho\{0, 1\}$	Moderate-high	0.5	0
ρ_V	$V_\rho\{0, 0.5\}$	No,Yes	0.5	0.5
L_A	$V_L\{-1, 0, 1\}$	Low-High	0	-1
T_c	$V_T\{0, 0.5\}$	Good-Poor	0	0

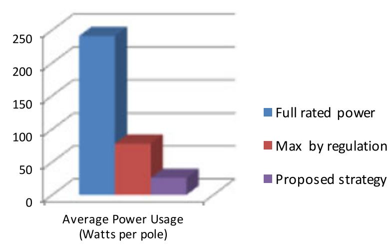

Fig. 4. Results of the Washington DC case study.

roadway, for instance, the direction in which the road ahead is turning. Specifically, the values of static roadway parameters used for Washington DC and Montgomery County, MD case studies are presented In Table 6.

The parameters in Table 6 are defined as follows, c is traffic composition, s is separation of carriageways, ρ is intersection density, ρ_V is parked vehicles, L_A is ambient luminance, and T_c is traffic control.

The traffic composition in Washington DC is expected to be mixed (vehicular and pedestrian) whereas, in rural Montgomery County it is expected to be mainly vehicular. Rural Montgomery County likely does not have separation of carriageways. The density of intersections in Washington is judged to be moderate whereas it is low for Montgomery County. By reference, the density of intersections in a place like Manhattan would be very high (value of 1). Finally, the level of ambient luminance in Washington is likely to be higher (value 0) than Montgomery County (value -1). Once again by reference, in densely populated areas, for example Manhattan, the ambient luminance would be even higher (value 1).

5. Results and Discussion

In this section, we present the results of the two case studies. Based on the light pole data, traffic data, and model discussed in Section 3, we derive the average usage (in Watts) per pole when the model is applied to produce traffic adaptive street light control. As reference we also provide results for average power usage (in Watts) using:

1) full rated power of the luminaires and,
2) light levels dimmed to provide $50lx$, the maximum light levels required by $CIE115:2010$.

These results are provided for Washington DC in Fig. 4 and for Montgomery County in Fig. 5.

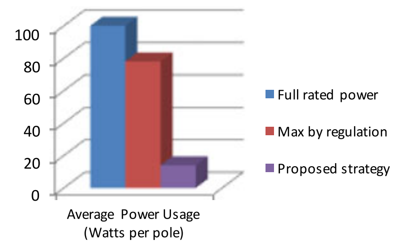

Fig. 5. Results of Montgomery County, MD, case study.

For Washington DC, an 89% power reduction is observed once the proposed strategy is implemented as opposed to the existing strategy, that is using full rated power. A power reduction of 66% is observed when the proposed strategy is compared with operating at max lux level at all times.

For Montgomery County, an 86% power reduction is observed once the proposed strategy is implemented as opposed to the existing strategy, that is using full rated power. A power reduction of 82% is observed when the proposed strategy is compared with operating at max lux level at all times.

Note that more traffic (impacting dynamic parameters) and higher ambient luminance (impacting static parameters) in Washington DC means greater light levels and less energy savings.

6. Conclusion

With increasing focus on energy conservation, the lighting industry is rapidly adopting new technologies, such as LEDs and controls for street-lighting maintenance and management. Although major savings can be incurred by adapting street lights based on traffic data, commonly used street-lighting control strategies still use schedule-based methods, which can be further optimized from a safety and savings perspectives, by adopting dynamics-based control strategy. The CIE street lighting level recommendations were deemed imprecise by noting that traffic flow and traffic density have a nonlinear dependence. In this paper, we present our approach to street light control that is based on online, adaptive parameter estimation of the Greenshields macroscopic traffic and the CIE 115:2010 models. Two case studies using light pole and traffic data for Washington DC and Montgomery County, MD, representing urban and rural roadway networks respectively, are implemented. When compared to maximum recommended lux levels by regulation, energy savings of 66% for Washington DC and as high as 82% for Montgomery County, MD, were observed. The differences in results in the two used case studies are mainly due to both static and dynamic factors, namely, more traffic and higher ambient luminance in Washington when compared to Montgomery County, MD.

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