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Street Lighting Optimal Dimming with Model Predictive Control

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***Abstract*— Street lighting dimming is adjustable to current micro-location conditions such as weather, road and pavement traffic type and density. With the trade-off goals of energy savings and required lighting quality, it is suitable for optimization problem formulation. The paper proposes a model predictive control for optimal dimming of street lighting adjustable to micro-location conditions and multiple spatial points of interest. Simplified mathematical model of street lighting ray tracing is utilized to capture expected illuminance in various points of interest in a three-dimensional space. Power percentage of luminaires is optimized based on predicted micro-location data and with imposed gradual rate of change. A joint street-wise dimming profile is adjusted to several points of interest for each luminaire as a reference tracking problem for optimizing the light demand trade-off in critical points from safety aspect, user comfort from social aspect and minimizing the overall consumption. The algorithm is verified on the realistic annual simulation for a case study of Kralja Tomislava street in City of Sisak, Croatia. The results show the potential of 31.94% less consumption compared with the currently operating street lighting.**

I. Introduction

Street lighting system is one of the most widespread infrastructures of the modern cities, crucial for public safety and life quality. It is technologically outdated and consumes up to 30% of the city electric energy [1], and therefore a suitable area for further energy efficiency improvements. The modernization of the system implies replacing the luminaires with Light-Emitting Diodes (LED), but also improvements in the control systems, remote-control capability and adaptation to working conditions.

Aiming to improve the energy efficiency and performance of the system, several research works have been carried out in the past two decades, mostly focusing on remote-control and application of new communication protocols. Recently, approaches also include LED street light modelling and adaptive and intelligent control design.

System architecture that enables adaptive remote control of public lighting is proposed in [2]. The results show savings of 25.64% while maintaining the maximum light intensity at peak traffic and pedestrian flows. In [3], an intelligent wireless communication system for LED streetlight management is presented. The system minimizes the investment cost of traditional wired approach and makes it dynamically adaptive to surrounding environment conditions.

Based on the I-V characteristics of the LED luminaire datasheet, voltage, current and resistor parameters were extracted to build a proposed mathematical model of the luminaire in [4]. In comparison with measurements-based approach, the proposed model showed better performance. Another mathematical model of the LED photo-electro voltage and current model is derived in [5]. The results of the model verification using two LED lamp chips indicated that the model is qualified for design and research purposes. Modelling of the LED light spatial distribution on the street surface with respect to the Cartesian coordinates of the points of interest, lamp position, height of the lamp, and angular distribution profile of lamp luminous intensity is reported in [6].

The authors of [7] propose regression, statistical, and neural prediction methods of the vehicular traffic flow data collected by a smart camera. A high potential energy saving is revealed from the experimental results without affecting the safety of traffic. To release the congestion during traffic peak-load, exponential, weighted, and simple moving average traffic prediction models are analyzed in [8]. The authors propose a control mechanism based on categorization and packet propagation to prevent the network from overloading, showing that weighted moving average model is most effective in reducing packet dropped. Based on the historical data of pedestrian movements collected by motion sensor, the authors of [9] propose a system that predicts the pedestrian activity and controls the streetlight intensity accordingly. The results obtained showed the effectiveness of the proposed system in securing the pedestrians safety, reducing the light pollution, and improving the energy efficiency of the system. Aiming to optimize the energy consumption of the streetlight system for better energy efficiency improvement, an embedded video processing-based strategy is proposed in [10]. An adaptive control scheme uses deep learning for off-peak and late-night hours. The movement of pedestrians and vehicles is detectable and exploitable for the adjustment of the lighting level, resulting in significant improvement of the energy efficiency.

A fuzzy logic based-controller is proposed in [11] for adjusting the brightness of photovoltaic-powered street luminaires with respect to future traffic forecast model based on real data and energy level of batteries. Simulation results

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indicate that the proposed control system ensures the street security and extend the autonomy of the system. Authors of [12] propose an artificial neural network control strategy to improve the energy efficiency of a residential street lighting area. The results obtained indicated that a 13.5% reduction of power consumption and 34% of unwanted utilization of the system.

In this paper, a centralized Model Predictive Control (MPC) algorithm for street lighting system is proposed considering micro-location conditions of weather, pedestrians, traffic, and street topology, denoted jointly as WPTS. Besides the flow density, the conditions also imply road and pavement users diversity, related to number of diverse spatial coordinates. Based on collected data, predictions of WPTS conditions are generated and used as inputs to modify the fundamental dimming profile. Together with derived ray tracing model of light propagation, the tracking MPC optimization problem is formulated. The concept is initially proposed in [13] for a 4-luminaire road segment and here extended for the whole street and long-term operation. The control system is simulated based on real case study of street geometry and data for the selected street in City of Sisak, Croatia. Results obtained for a one-year period show the effectiveness of the proposed control.

The paper is organized as follows. Section II presents light propagation mathematical model and MPC. The implementation aspects and case study is elaborated in Section III. Results are presented and discussed in Section IV, followed by conclusions in Section V.

II. Model Predictive Control of Street Lighting

A. Mathematical Model

For optimal three-dimensional spatial lighting, often also referred to as vertical lighting, we propose a MPC algorithm to adjust the illuminance intensity at a chosen set of points of interest on the street surface. For this, we first derive a mathematical relation between a luminaire as the light source and the illuminance E_p at arbitrary selected points of interest p defined with Cartesian coordinates (x, y, z). The model is based on [6] and also includes luminaire geometric data, such as height h and boom length d, and light source characteristic, i.e. luminous intensity I. A single point of interest p is influenced by n_s luminaires of index i and results in superposed contribution:

$$E_p(x,y,z) = \sum_{i=1}^{n_s} \frac{I_i \cdot h_i}{\left[(x_i^2) + (y_i - d_i)^2 + (h_i - z_i)^2\right]^{\frac{3}{2}}}, \quad (1)$$

where I is dependent of photometric and azimuth angle, which are related as trigonometric functions of (x, y, z) [6],[13].

In discrete time state-space representation, such model obtains the form:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k, \\ y_k &= Cx_k, \end{aligned} \quad (2)$$

where:

- $k \in \mathbb{Z}$ is the sampling time index.
- $x_k \in \mathbb{R}^m$ is the system state vector (the illuminance intensity level at each point of interest, $x_k = \left[E_1, E_2, \ldots, E_m\right]_k^\top$) with m as the number of the observed points in the street.
- $u_k \in \mathbb{R}^n$ is the system input vector i.e., vector of luminous intensity level of each contributing streetlight luminaire, $u_k = \left[I_1, I_2, \ldots, I_n\right]_k^\top$ with n as the number of the luminaires in the street.
- $y_k \in \mathbb{R}^m$.

By substituting lamp parameters and the Cartesian coordinates of the observed points of interest p in the illuminance model from (2), a general road segment ns_i between luminaires i and $i+1$, shown in Fig. 1, is modeled as:

$$x_{k+1}^{ns_i} = A^{ns_i} x_k^{ns_i} + B^{ns_i} u^{ns_i}, \quad (3)$$

with $x^{ns_i} \in \mathbb{R}^{m_s} = [E_A^{ns_i}, ..., E_J^{ns_i}]^\top$ representing illuminance in the observed points of interest, influenced by luminaires $u^{ns_i} \in \mathbb{R}^{n_s} = [I_{i-1}^{ns_i},\ I_i^{ns_i},\ I_{i+1}^{ns_i},\ I_{i+2}^{ns_i}]^\top$. With more lamps influencing x, vector u is augmented correspondingly. Street composition determines only the mutual Cartesian relations of lamps and observed points, and reflects in B^{ns_i}.

Since light propagation is instantaneous, the model is static, i.e. $A = 0$ in (2) and correspondingly in (3). However, the model is extendable for moving objects in which case A is dynamic and B non-linear, or for weather effects (fog) in which case B is time-varying. For simplicity, here we focus on the static model.

Whole street is further modeled by stacking the segments:

$$\begin{aligned} &x = [x^{ns_i \top},\ x^{ns_{i+1} \top}, ..., x^{ns_{i+n} \top}]^\top, \\ &u = \bigcup_{i}^{n} u^{ns_i} = \left[I_1, I_2, \ldots, I_n\right]^\top, \quad (4) \\ &A = \begin{bmatrix} A^{ns_i} & 0' & 0' \\ 0' & A^{ns_{i+1}} & 0' \\ 0' & 0' & \ddots \end{bmatrix},\ B = \begin{bmatrix} B^{ns_i} & 0^{n_s} & 0^{n_s} \\ 0^{n_s} & B^{ns_{i+1}} & 0^{n_s} \\ 0^{n_s} & 0^{n_s} & \ddots \end{bmatrix}, \end{aligned}$$

where $0' = 0^{m_s \times m_s}$. Note that 0^{n_s} is a vector.

B. Model Predictive Control

The collected and processed data of WPTS conditions are used to generate prediction data for a prediction horizon N with a time resolution of T_s. Based on the prediction data, a new adaptive dimming profile, and therefore, a dynamic reference x^{ref} is obtained at a predetermined set of points of interest p. The prediction data is generated comparing to a respective historical WPTS data. Each prediction is generated by a modelling method using one of group of methods consisting of physical models, machine learning methods, or neural networks, which are focus of our paper [14].

Delivered illuminance intensity at any point of interest on the street surface with respect to WPTS conditions is

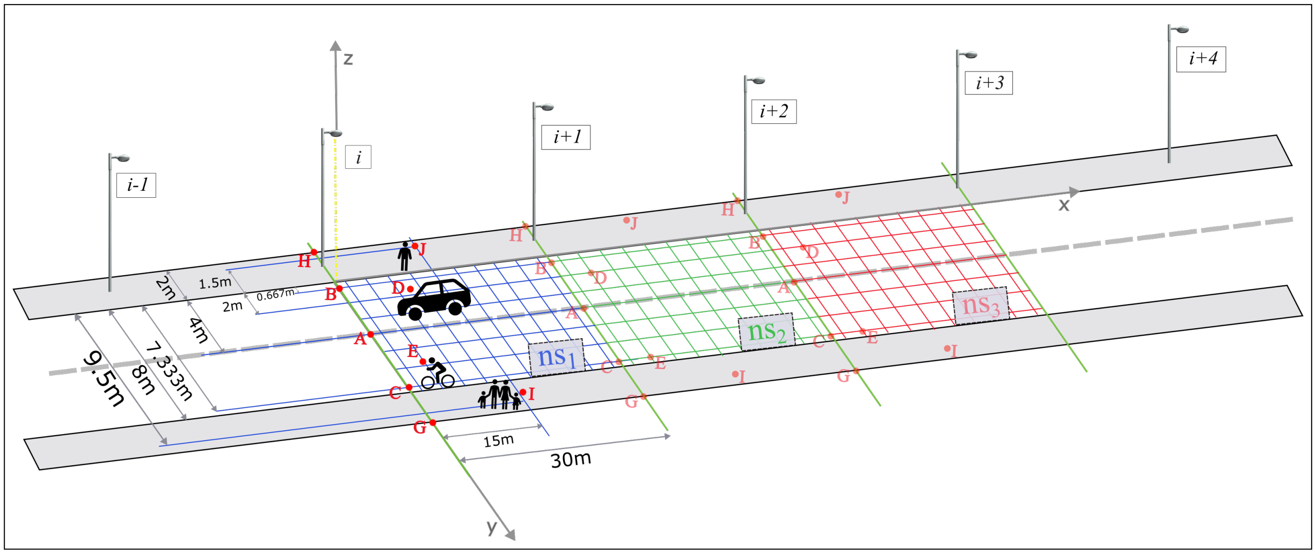

Fig. 1: Street segment with contributing luminaires and points of interest

formulated as an MPC reference tracking problem:

$$
\begin{aligned}
&\min_{u_{i,k}} \sum_{k=1}^{N}\sum_{j=1}^{m}\sum_{i=1}^{n} w_j|x_{j,k}-x_{j,k}^{ref}| + w_u u_{i,k},\\
&\text{s.t.}\\
&x_{j,k} \geq x_{min}, \qquad j \in S,\\
&x_{j,k}^{ref} = f(j,k,v_k),\\
&x_{j,k+1} = Ax_{j,k} + Bu_{i,k},\\
&y_{j,k} = Cx_{j,k},\\
&0 \leq u_{i,k} \leq u_{max},\\
&\Delta u_{min} \leq u_{k+1} - u_k \leq \Delta u_{max}
\end{aligned}
\tag{5}
$$

where:

- n: total number of luminaires
- i: luminaire index
- m: total number of points of interest p
- j: point of interest index
- N: prediction horizon
- k: discrete time step index
- u: control variable as lamp power (0-100%)
- x: state variable as illuminance intensity at the point of interest p
- $x_{j,k}^{ref}$: dynamic desired illuminance intensities at points of interest p
- w: weighting coefficients (priorities)
- f: prediction and estimation of the desired lighting level at j point of interest in weather conditions v_k
- S: subset of p for which the quality of lighting (norms) strictly applies
- x_{min}: Minimum allowed lighting intensity stemming from the street lighting norms
- u_{max}: Maximum permissible light source intensity
- Δu_{min}: Minimum power change as gradual decrease
- Δu_{max}: Maximum power change as gradual increase

Introduction of Δu implies extension of x with past values of u, and A from (2) is no longer static. The weighing factor w_j is chosen to empirically impose priority of points of interest, i.e. critical and less important ones, together with the selection of j point of interest and its 3D position in the street. The w_u emphasize importance of power savings in trade-off to trajectory following part. Setting $x_{j,k}^{ref} = 0$ implies light pollution reduction in chosen j point of interest.

III. Case Study and Implementation

The approach is validated for King Tomislav Street (Fig. 2) in the City of Sisak, Croatia, considering the available data of WPTS and current dimming profile of the street lighting system. The specifications of the installed luminaires PrecisionLux2 LE-CS-80 manufacturer LED Elektronika Ltd. is given in Table I.

TABLE I. PrecisionLux2 LE-CS-80 specifications.

Technical specification	Value
P	80 W
Φ_{Lamp}	9694 lm
$\Phi_{Luminaire}$	8918 lm
η	92.00 lm
Luminous efficacy	111.5 lm/W
Pole distance	30.000 m
Light spot height	8.000 m
Light spot overhang	0.000 m
Boom inclination	0.0°

A schematic representation of three street segments is shown in Fig. 1. The distance between any two successive lamps for King Tomislav Street is 30 m, the height of the lamp is $h = 8$ m, the light point overhang is 0 m, the boom inclination is 0 m, and boom length is $d = 0.1$ m. The Cartesian x, y, and z coordinates of the selected set of points of interest {A, B, C, D, E, G, H, I, J} representing vehicles, cyclists, pedestrian (children, elderly, disabled, etc.) are shown in Table II.

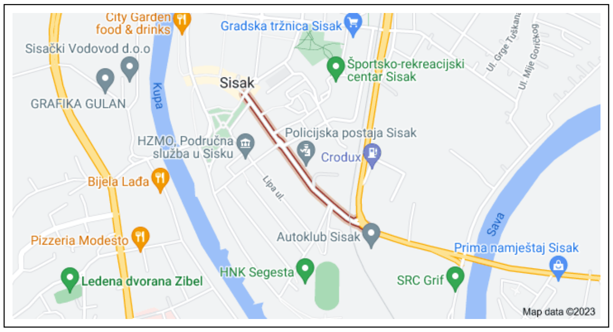

Fig. 2: Case study street of King Tomislav Street

This illuminance distribution model is verified based on a data collected from two street segments of King Tomislav and J. J. Strossmayer Streets in the City of Sisak, Croatia. The model shows high accuracy with deviation less than 0.3% for average error of 60 points in each segment with four contributing luminaires [13] when compared to professional lighting ray tracing software.

TABLE II. Cartesian coordinates of points of interest A-J.

(x,y,z)	I1	I2	I3	I4
A	(0,4,0)	(-30,4,0)	(30,4,0)	(-60,4,0)
B	(0,0.667,0)	(-30,0.667,0)	(30,0.667,0)	(60,0.667,0)
C	(0,7.333,0)	(-30,7.333,0)	(30,7.333,0)	(-60,7.333,0)
D	(4.5,2,1.2)	(-25.5,2,1.2)	(34.5,2,1.2)	(-55.5,2,1.2)
E	(4.5,7.333,1.5)	(-25.5,7.333,1.5)	(34.5,7.333,1.5)	(-55.5,7.333,1.5)
G	(0,10,0)	(-30,10,0)	(30,10,0)	(-60,10,0)
H	(0,-2,0)	(-30,-2,0)	(30,-2,0)	(-60,-2,0)
I	(15,9.5,1)	(-15,9.5,1)	(45,9.5,1)	(-45,9.5,1)
J	(15,-1.5,1.7)	(-15,-1.5,1.7)	(45,-1.5,1.7)	(-45,-1.5,1.7)

Using the data from tables I and II, the model (2) is obtained, given e.g. for first five points $p \in \{\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}, \mathrm{E}\}$ of segment ns_i influenced by four luminaires:

$$\underbrace{\begin{bmatrix} x_{A,k+1} \\ x_{B,k+1} \\ x_{C,k+1} \\ x_{D,k+1} \\ x_{E,k+1} \end{bmatrix}}_{x_{k+1}} = \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_{A,k} \\ x_{B,k} \\ x_{C,k} \\ x_{D,k} \\ x_{E,k} \end{bmatrix}}_{x_k} + \underbrace{\begin{bmatrix} 0.0112 & 0.0003 & 0.0003 & 0.0000 \\ 0.0155 & 0.0003 & 0.0003 & 0.0000 \\ 0.0063 & 0.0002 & 0.0002 & 0.0000 \\ 0.0135 & 0.0004 & 0.0002 & 0.0000 \\ 0.0064 & 0.0004 & 0.0002 & 0.0000 \end{bmatrix}}_{B} \times \underbrace{\begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix}}_{u_k}, \tag{6}$$

$$\underbrace{\begin{bmatrix} y_{A,k} \\ y_{B,k} \\ y_{C,k} \\ y_{D,k} \\ y_{E,k} \end{bmatrix}}_{y_k} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{C} \times \underbrace{\begin{bmatrix} x_{A,k} \\ x_{B,k} \\ x_{C,k} \\ x_{D,k} \\ x_{E,k} \end{bmatrix}}_{x_k}.$$

Based on acquired WPTS data, the representative validation scenarios are selected to demonstrate recurring road conditions at selected micro-location. Each scenario is determined by a year period, traffic and pedestrian density and diverse weather conditions typical for the selected location. Traffic density is categorized between 0 and 10, corresponding to empty road and full traffic jam, respectively. Characteristic weather conditions for selected location are: clear and dry weather, rain, snow and fog. Selected weather conditions are characterized by temperature, precipitation, visibility and humidity information.

TABLE III. Adaptive dimming profile (predetermined streetlight dimming scenario)

	Road conditions	Thresholds	Dimming profile	
1	Clear, dry Light traffic Few pedestrians	precipitation = 0 visibility $\geq$ 10 000 traffic density $<$ 4 pedestrians_total $<$ 10.0	D1	0.3@80% 0.7@20%
2	Clear, dry Moderate traffic Moderate pedestrians	precipitation = 0 visibility $\geq$ 10 000 traffic density $\geq$ 4 traffic density $<$ 8 pedestrian_total $\geq$ 10.0 pedestrian_total $\leq$ 50.0	D2	0.3@90% 0.7@20%
3	Clear, dry Severe traffic Many pedestrians	precipitation = 0 visibility $\geq$ 10 000 traffic density $>$ 8 pedestrians_total $>$ 50.0	D3	0.3@100% 0.7@30%
4	Rain Moderate traffic Moderate pedestrians	precipitation $>$ 0 humidity $\geq$ 90 visibility $\leq$ 10 000 traffic density $\geq$ 4 traffic density $<$ 8 pedestrian_total $\geq$ 10.0 pedestrian_total $\leq$ 50.0	D4	0.3@100% 0.7@40%
5	Snow Moderate traffic Moderate pedestrians	precipitation $>$ 0 humidity $\geq$ 90 temperature $<$ 0 visibility $\leq$ 10 000 traffic density $\geq$ 4 traffic density $<$ 8 pedestrian_total $\geq$ 10.0 pedestrian_total $\leq$ 50.0	D5	0.3@80% 0.7@40%
6	Fog Moderate traffic Moderate pedestrians	precipitation $=$ 0 humidity $\geq$ 90 temperature $\leq$ 10 visibility $\leq$ 10 000 traffic density $\geq$ 4 traffic density $<$ 8 pedestrian_total $\geq$ 10.0 pedestrian_total $\leq$ 50.0	D6	0.3@90% 0.7@40%

According to the selected validation scenarios, the new dimming profile is established for each scenario individually by the lighting operator to ensure specific adaptation of light intensity to current road conditions. The list of representative simulation scenarios with the new adaptive dimming profile is shown in Table III. Such general dimming profile is further fine-tuned for individual road segments and for individual points of interest such that x^{ref} is formed.

For the complete street, the segments are stacked along the x-axis positive direction. In particular, 3 km long case study street with 100 luminaires and the distance between two consecutive ones of 30 m, the street is divided into 1000 segments. For each segment, four lamps are contributing to provide the required lighting level on the street surface for 9 selected points of interest. Also, a single luminaire contributes to 4 segments or 36 points of interests.

The above-mentioned case and corresponding problem dimensions are for the highest customization of the street lighting, implying that every street luminaire can monitor its own WPTS data and observe own set of points of interest with corresponding trajectory tracking weights. The dimensions are further stacked over the prediction horizon, leading to large dimensions of the problem. Simplifications are applicable and various scenarios are possible, stemming down to the whole street being considered as a single segment, or parting the street to representative groups of segments such as crossroads, pedestrian crossings, vicinity of vital buildings, and regular, non-critical segments.

A. *Micro-location conditions*

In the normal practice of the street lighting control system, the system operator applies specific dimming profile for different street categories in the city. These profiles are set to the best practice of the operator, following from road location and traffic density. Those are usually set to a higher level in the evenings and mornings when traffic is more dense, and to a lower one throughout the night. In particular for a M3 category road of King Tomislav Street, shown in Fig. 2, current dimming profile is set as 15%-70%-15% of time at 100%-40%-100% of power, denoted as 0.3@100%, 0.7@40%, obtained from our industry partner. The time of operation (on and off) of street lighting is calendar-dependent, defined with sunset and sunrise times.

The adjustment of the lighting level considers WPTS data of weather conditions, pedestrian diversity and volume, traffic volume and road conditions as well as the current applied dimming profile. Therefore, the data of WPTS and current dimming profile is collected for May 2021 to May 2022.

To define the street users requirements and preferences, a survey of 245 people is conducted with the aim to determine drivers and pedestrians visual demands and evaluate the quality of current public lighting setup. The survey considered age, gender, physical disabilities, and habits.

Weather conditions are collected for a one-year period from local weather station in City of Sisak. Road traffic conditions are taken from the commercial navigation service. The collected data were extracted to tables, cleaned, processed, and saved to the simulation environment.

IV. Results

Results are obtained in MATLAB/Simulink with time horizon of 6 hours ahead, i.e., the prediction horizon is $N = 72$ with a sampling time step of 5 minutes. Gradual rate of change constraints are chosen as $\Delta u_{min} = -250$ W and $\Delta u_{max} = 250$ W for a sample time T_s, set as 5 minutes.

The MPC algorithm is simulated for one-year period, with on-site micro-location data from May 2021 to May 2022, for two cases: $i)$ the currently operating case and using the current dimming profile denoted as 'Current' and $ii)$ MPC with adaptive dimming profile to adjust the illuminance intensities at the selected set of points of interest according to specific dimming profiles and WPTS data, denoted as 'MPC'.

Figure 3 shows the daily energy consumption of the street lighting system of 100 considered lamps with current dimming profile and the proposed MPC approach for one-year simulation time. The trend correlates with daylight duration, resulting in higher consumption during winter period. Adaptable dimming to micro-location data evidently consumes less energy. It can also be observed that the energy consumption with adaptable dimming (MPC) is less uniform throughout the year as a result of variable WPTS data and corresponding scenarios from Table III.

Two representative weeks from summer (August 2-8, 2021) and a winter period (January 17-23, 2022) are presented in figures 4 and 5. The figures show WPTS micro-location conditions of traffic and pedestrian density, and weather data of temperature, humidity, visibility and precipitation. As mentioned before, traffic data is taken from navigational service and show expressed morning rush hours and differences between working and non-working days. It also shows higher traffic during summer period. Pedestrian data is taken from survey for working and non-working days, and therefore visibly repetitive as not being real-time acquired. Weather difference is evidently expressed, with winter period having intervals of reduced visibility and high humidity but no precipitation, resulting in fog scenario selection of dimming profile. Low temperature in winter period results in snow-risk scenarios and higher illumination throughout the night. This is also visible in Fig. 3 as the expressed peak consumption during winter days.

Total consumed electric energy for a single luminaire and one-year operation is summed as percentage operation for 5 min intervals and extended to 1h, then summed for the whole year of 8760 hours. For the presented case, the total consumption of current operation is 186.86 kWh for e.g. luminaire 1 and 18.686 MWh for the whole street. The total yearly consumption of MPC approach is 127.19 kWh for e.g. luminaire 1 and 13.705 MWh for the whole street. In relative terms, consumption of luminaire 1 is reduced by 31.93% and the total street consumption by 26.65%. The difference occur since some of the street segments, such as pedestrian crossing and crossroads, are selected as safety-critical ones

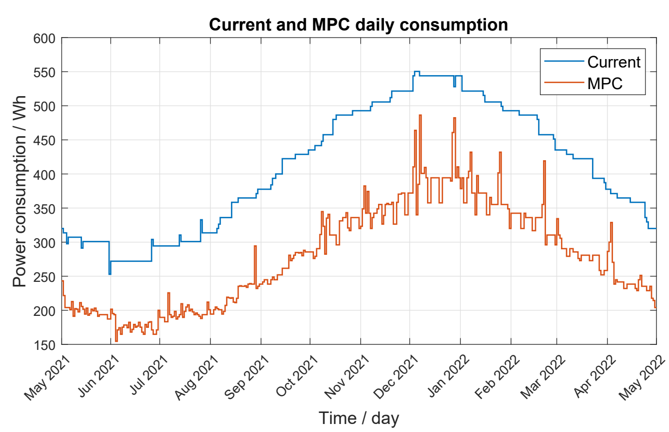

Fig. 3: Daily power consumption for one luminaire.

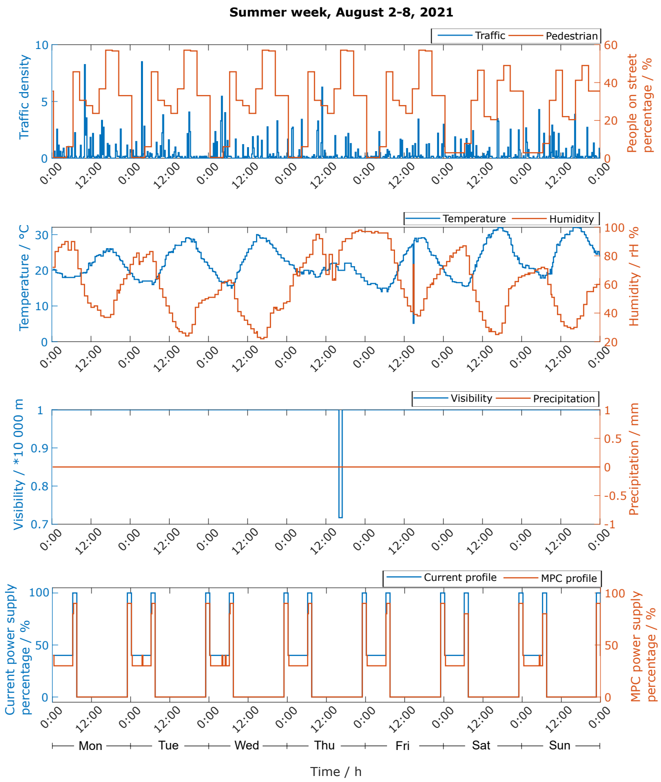

Fig. 4: Dimming profiles for exemplary summer week

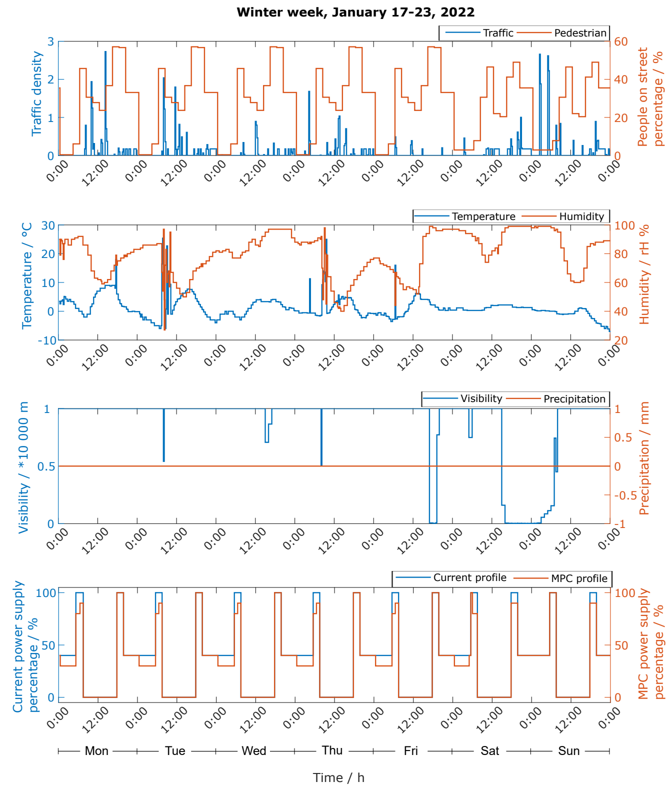

Fig. 5: Dimming profiles for exemplary winter week

and therefore require higher level of illuminance intensity.

Finally, from the perspective of obtaining savings, it comes to the decision on the dimming profiles and, more specifically, the level of the amount of light on the street for the cases of low or no traffic or pedestrians.

V. Conclusion

The paper proposes an MPC strategy for street lighting formulated as a trajectory tracking problem with referent dimming profiles specific for selected spatial points of interest on the street, adjustable to road and pedestrian traffic flow and diversity, and weather conditions. The algorithm is highly adjustable and offers significant opportunity in energy efficiency, safety, and lighting comfort, all predictively adjustable to on-site conditions. The effectiveness of the approach is validated in 1-year simulation based on real test site data and micro-location conditions, resulting in up to 31.93% consumption reduction for the presented case.

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