ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

ENABLING ADAPTIVE ROAD LIGHTING THROUGH LIGHTING CLASS PREDICTION WITH REAL TIME AND HISTORICAL DATA

M.Sc. THESIS

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Department of Energy Science and Technology

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JULY 2024

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

GERÇEK ZAMANLI VE GEÇMİŞ VERİYE DAYANAN AYDINLATMA SINIFI TAHMİNİ İLE UYARLANABİLİR YOL AYDINLATMASININ SAĞLANMASI

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TEMMUZ 2024

Hasan Mert TOKGÖZ, a M.Sc. student of İTU Graduate School 301211018 successfully defended the thesis/dissertation entitled "ENABLING ADAPTIVE ROAD LIGHTING THROUGH LIGHTING CLASS PREDICTION WITH REAL TIME AND HISTORICAL DATA", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 24 May 2024
Date of Defense : 2 July 2024

FOREWORD

The master's thesis process was very useful for me. I gained a lot of knowledge and skills during this process. I would like to express my gratitude to my advisor Asst. Prof. Dr. Mustafa Berker Yurtseven, who made a great contribution to me both during the courses I took from him and during my thesis work. I would also like to thank Prof. Dr. Sermin Onaygil and Prof. Dr. Önder Güler or sharing their valuable ideas, knowledge and experiences in my thesis work.

I would like to express my heartfelt thanks to my girlfriend İlkin Yapıcı, who was a source of motivation and inspiration for me to both start and complete a MSc program. I would also like to express my gratitude and respect to my family, who supported me throughout my whole education life.

May 2024

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ABBREVIATIONS

ANN **:** Artificial neural network
ARL **:** Adaptive road lighting
CEN : European Committee for Standardization
CIE : International Commission on Illumination
FN : False negative
FP : False positive
HPS **:** High-pressure sodium
IoT **:** Internet of things
LED **:** Light emitting diode
LSTM **:** Long short-term memory
MH **:** Metal halide
ML **:** Machine learning
PIR **:** Passive infrared
RF **:** Random forest
RSS **:** Received signal strengths
SR **:** Surrounding ratio
TI **:** Threshold increment
TN **:** True negative
TP **:** True positive
TSE **:** Turkish Standards Institution
xGBoost **:** Extra gradient boosting

SYMBOLS

L	**:** Luminance
L_{min}	**:** Minimum luminance
L_{av}	**:** Average luminance
U_l	**:** Longitudinal uniformity
U_o	**:** Overall uniformity
V_w	: Weighting value
V_{ws}	: Total weighting value

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ENABLING ADAPTIVE ROAD LIGHTING THROUGH LIGHTING CLASS PREDICTION WITH REAL TIME AND HISTORICAL DATA

SUMMARY

Road lighting plays a crucial role in transportation systems as it significantly contributes to ensuring safety for road users during hours when there is not enough daylight. A road lighting system that meets prescribed standards aims to prevent traffic accidents that may occur as a result of insufficient lighting while providing visual comfort conditions for road users. In these days when it is necessary strategize and execute energy consumption reduction plans in various areas in order to use limited energy resources more efficiently. As a substantial contributor to urban energy consumption, road lighting is currently undergoing the development of sustainable and energy-efficient systems through the formulation of standards and implementation of projects.

The first method that comes to mind in order to reduce energy consumption is to replace existing luminaries with LED luminaries. It has been proven in many studies that road lighting made with LED luminaries is much more energy efficient compared to other types of light sources. One of the benefits of LEDs compared to other conventional lamp varieties is the ability to regulate the amount of luminous flux emitted by the luminaries. By utilizing the dimming feature, it is possible to provide illumination at different levels for different needs from the same light source.

Adaptive road lighting (ARL) adjusts luminous flux and luminance levels based on environmental conditions and traffic flow, enhancing energy efficiency and driving safety by ensuring optimal lighting conditions. Through the utilization of environmental data and traffic analysis, these systems are capable of adapting lighting levels to ensure optimal illumination while simultaneously lowering energy usage. The effectiveness of such systems largely depends on accurate predictions of traffic data and weather conditions. Therefore, to ensure the effectiveness of adaptive road lighting systems, it is crucial to have a comprehensive understanding of the road's characteristics. By integrating the real-time traffic flow data with the historical data gathered from the road sensors, more precise predictions can be made. In addition to ARL systems in the form of simulation or prototypes, which have become increasingly popular in recent years, it is essential to provide guidance for sample applications, reports, and specification studies.

This study explores different strategies for analyzing traffic data, ranging from traditional statistical models to advanced machine learning algorithms. It highlights the significance of various factors, including historical traffic data, weather conditions, and road topology, in the development of precise prediction models. The effectiveness of these prediction techniques in diverse urban environments is presented with case studies. In this study, the focus is on exploring various strategies that can be employed for real-time data processing, model updating, and decision-making algorithms. The primary aim of these strategies is to optimize lighting adjustments by utilizing

predicted lighting class. Additionally, the study investigates the potential synergies that can be derived from integrating these strategies with smart city initiatives and traffic management systems. By combining predictiveanalytics with intelligent lighting infrastructure, this research highlights the wider impact that can be achieved, underscoring the improvement in overall efficiency and effectiveness.

The road chosen as the case study is located within the city and provides services in two different directions. It consists of a total of six lanes, each is 3 meters wide. The lighting class of the road had been determined as M2. In order to provide the specified lighting class, the luminaires were placed on 13-meter-high lighting poles with a distance of 40 meters between them. Traffic flow rate and vehicle speed data taken with 2-minute intervals for each lane on the road has been recorded for a year and new data continues to be collected.

In order to identify appropriate methodologies for this objective, existing traffic data of the pilot road were visualized, and a model was developed that can estimate the lighting class for a desired period from a selected time of the day with minimum error using machine learning algorithms. In the most successful models created, the accuracy of hourly lighting class predictions exceeds 97%. In addition to predicting lighting classes, the calculation of energy consumption based on the established lighting scenarios was conducted, and the energy saving rates for the suggested adaptive road lighting system were explicitly outlined. Given the potential decrease in driving visibility and comfort during rainy weather, it has been determined that the road lighting setup will adhere to M2 lighting class requirements at all times, with the suspension of ARL scenarios.

This research results that the transformation of road lighting systems into adaptive road lighting through automation strategies aligned with traffic flow rates, vehicle speeds, and meteorological conditions could result in elevated rates of energy savings. Overall, this study provides a comprehensive analysis of the role of lighting class prediction in enhancing adaptive road lighting systems and, contributes to advancing knowledge in optimizing adaptive road lighting systems for energy efficiency and driving safety, with potential practical applications in smart city infrastructure. A detailed field study needs to be continued to ensure that the applied scenarios and strategies do not adversely affect traffic safety and visual comfort conditions of road users. The need for standardized data collection and sampling protocols, storage of big data, and privacy issues will be some of the challenges and topics of future discussion in this field.

GERÇEK ZAMANLI VE GEÇMİŞ VERİYE DAYANAN AYDINLATMA SINIFI TAHMİNİ İLE UYARLANABİLİR YOL AYDINLATMASININ SAĞLANMASI

ÖZET

Yol aydınlatması, gün ışığının yeterli olmadığı saatlerde yol kullanıcılarının güvenliğinin sağlanmasına önemli katkı sağladığından ulaşım sistemlerinde oldukça önemli bir rol oynamaktadır. Öngörülen standartlara uygun bir yol aydınlatma sistemi, yol kullanıcılarına görsel konfor koşulları sağlarken, yetersiz aydınlatma sonucu oluşabilecek trafik kazalarının önlenmesini amaçlamaktadır. Günümüzde sınırlı enerji kaynaklarının daha verimli kullanılabilmesi için çeşitli alanlarda enerji tüketimi tasarruf planlarının oluşturulup uygulanması gerekmektedir. Kentsel enerji tüketiminde göz ardı edilemeyecek bir paya sahip olan yol aydınlatması sistemleri, standartların oluşturulması ve verimlilik projelerin uygulanması yoluyla sürdürülebilir ve enerji verimli sistemler haline getirilme potansiyeline sahiptir.

Türkiye'de yol aydınlatma sistemlerinde çoğunlukla enerji tüketimi nispeten daha yüksek olan yüksek basınçlı sodyum buharlı lambalar kullanıldığından, enerji tüketimini azaltmak için akla gelen ilk yöntem, mevcut armatürlerin LED armatürlerle değiştirilmesi olmalıdır. LED armatürlerle yapılan yol aydınlatmasının diğer ışık kaynaklarına göre çok daha verimli olduğu birçok çalışmayla kanıtlanmıştır. LED lambaların diğer lamba çeşitlerine göre avantajlarından biri de armatürün yaydığı ışık akısı miktarının ayarlanabilmesidir. Dimleme özelliğinden faydalanılarak aynı ışık kaynağından farklı ihtiyaçlara yönelik farklı seviyelerde aydınlatma sağlanması mümkündür.

Uyarlanabilir yol aydınlatması (ARL), çevre koşullarına ve trafik akışına göre aydınlatma ve parlaklık seviyelerini ayarlayıp en uygun aydınlatma koşullarını sağlayarak enerji verimliliğini ve sürüş güvenliğini artırır. Çevresel verilerden ve trafik analizinden faydalanan bu sistemler, enerji tüketimini azaltırken aynı zamanda optimum aydınlatmayı sağlama yeteneğine sahiptir. Bu tür sistemlerin etkinliği büyük ölçüde trafik verilerinin doğru tahminlerine bağlıdır. Bu nedenle, uyarlanabilir yol aydınlatma sistemlerinin etkinliğini sağlamak için yolun özelliklerine ilişkin kapsamlı bir anlayışa sahip olmak çok önemlidir. Gerçek zamanlı trafik akışı verilerinin, yol sensörlerinden toplanan geçmiş verilerle entegre edilmesiyle daha kesin tahminler yapılabilmektedir. Verilerin bu şekilde birleştirilmesi, yol koşullarının daha doğru bir şekilde değerlendirilmesine olanak tanıyarak aydınlatma ayarlarının en uygun şekilde yapılmasını kolaylaştırır. Bu araştırmanın arkasındaki temel itici güç, literatürde uluslararası standartlara göre gerçek yol kurulumlarında kullanılan ARL çalışmalarının sayısının yetersiz olmasıdır. Son yıllarda giderek popüler hale gelen simülasyon veya prototip şeklindeki ARL sistemlerinin yanı sıra örnek uygulamalar, raporlar ve spesifikasyon çalışmaları için de yol gösterici bir çalışma ortaya koymak amaçlanmıştır.

Önerilen yöntemlerin henüz istenilen seviyeye ulaşmaması ve pilot uygulamaların eksikliği, yoğun trafik akışı olan bir yolda uygulandıklarında hatalara sebebiyet

vermeleri sonucu tespit edilmiştir. Bu eksiklik, trafik yoğunluğunun ve akış hızının yüksek olduğu yollarda aydınlatma sınıfı tahminindeki hataların en aza indirilmesi için yeni modellerin oluşturulmasının gerekli olduğu sonucunu doğurmuştur. Gözlemlenen uyumsuzluk, mevcut metodolojilerin başlangıçta daha düşük trafik hacmi ve daha az sayıda şeride sahip yollarda uygulamaya yönelik olması gerçeğine atfedilebilir.

Bu çalışma, trafik verilerini analiz etmek için geleneksel istatistiksel modellerden gelişmiş makine öğrenimi algoritmalarına kadar farklı stratejileri araştırmaktadır. Kesin tahmin modellerinin geliştirilmesinde geçmiş trafik verileri, hava koşulları ve yol topolojisi dahil olmak üzere çeşitli faktörlerin önemini vurgulamaktadır. Bu tahmin tekniklerinin etkinliği örnek olarak seçilen yol üzerinde gerçekleştirilen çalışmalar ile sunulmaktadır. Bu çalışmada, gerçek zamanlı veri işleme, model güncelleme ve karar verme algoritmaları için kullanılabilecek çeşitli stratejilerin araştırılmasına odaklanılmaktadır. Bu stratejilerin temel amacı, öngörülen aydınlatma sınıfını kullanarak aydınlatma çıktılarını yol ihtiyaçlarına göre optimize etmektir. Ayrıca çalışma, bu stratejilerin akıllı şehir ve trafik yönetim sistemleri ile entegre edilmesinde elde edilebilecek potansiyel sinerjileri de araştırmaktadır. Tahmine dayalı analitiği akıllı aydınlatma altyapısıyla birleştirerek elde edilebilecek daha geniş etkiyi, genel verimlilik ve etkinlikteki iyileşmeyi ortaya sunmaktadır.

Örnek olarak seçilen yol şehir içerisinde yer almakta olup iki farklı yönde hizmet vermektedir. Her biri 3 metre genişliğinde toplam altı şeritten oluşmaktadır. İlgili yolun varsayılan aydınlatma sınıfı standartlar ve teknik raporlar ile uyumlu olacak şekilde M2 olarak belirlenmiştir. Belirlenen aydınlatma sınıfını sağlamak amacıyla LED armatürler 13 metre yüksekliğindeki aydınlatma direkleri üzerine aralarında 40 metre mesafe olacak şekilde yerleştirilmiştir. Yoldaki her şerit için 2 dakika aralıklarla alınan trafik akış hızı ve araç hızı verileri bir yıldır kayıt altına alınmakta ve yeni verilerin toplanmasına devam edilmektedir. Örnek olarak seçilen yol, aydınlatmaya ihtiyaç duyulan her saatte M2 aydınlatma sınıfına göre aydınlatılmasına rağmen, bu yolda yeterli aydınlatma düzeyini sağlamak için yapılan veri analizi çalışmaları sonucunda belirli zamanlarda M3 ve M4 aydınlatma sınıflarının da kullanılabileceği anlaşılmıştır. Bu zamanların belirlenmesi için CEN/TR 13201-1 teknik raporundaki M aydınlatma sınıfı belirleme parametreleri kullanılmıştır. Teknik raporda dinamik parametre olarak tanımlanan trafik hacminin yanı sıra ortalama araç hızı verisi ve bu veriye bağlı olarak da görsel kılavuzlama parametresi gerekli M aydınlatma sınıfının anlık değişken olmasını gerektiren diğer dinamik parametreler olarak varsayılmıştır.

Bu amaca uygun metodolojilerin belirlenmesi için örnek yolun mevcut trafik verileri görselleştirilmiş ve iki farklı yaklaşım ile uyarlanabilir aydınlatma stratejilerinin uygulanabileceği kararlaştırılmıştır. Bunlardan ilki trafik akış hızı ve araç hızlarının ortalama değerlerine göre oluşturulan istatistiksel ARL yaklaşımıdır. Bu yaklaşımda her mevsim için hem haftaiçi günleri hem de tatil günlerinin ortalama trafik verileri kullanılarak önceden programlanması planlanan sekiz ayrı yol aydınlatması senaryosu oluşturulmuştur. Her senaryo için aydınlatma sınıfının değiştirileceği saatler belirlenmiş ve grafiklere dökülmüştür. Bu yaklaşım sonucu yıl boyunca M2 aydınlatma sınıfında yapılacak sabit bir aydınlatma sistemine göre yıllık elektrik tüketiminde %29 civarı tasarruf sağlanmıştır fakat senaryo boyunca uygulanacak olan aydınlatma sınıfları gerçek veriler ile karşılaştırıldığında görülmüştür ki önceden planlanıp uygulanan aydınlatma sınıflarında genel olarak aydınlatmaya ihtiyaç duyulan saatlerin %15,5'inde hatalı aydınlatma yapılmıştır. Bu yaklaşımın uygulanması halinde gerçek verisi bulunan yıl boyunca yaklaşık olarak 338 saat yetersiz aydınlatma yapılacaktır.

İkinci yaklaşım için makine öğrenmesi algoritmaları kullanılarak günün seçilen bir saatinden istenilen süre için aydınlatma sınıfını minimum hatayla ve hızlı bir şekilde tahmin edebilecek bir model geliştirilmiştir. Model girdileri olarak ay, gün, saat, dakika gibi tarih bilgilerinin yanı sıra haftanın günü, iş günü veya okul günü olup olmadığına dair bilgi ve de son olarak toplanan on trafik akış hızı ve ortalama araç hızı verileri kullanılmıştır. Bir çok farklı regresyon ve sınıflandırma modelinin denenmesinin ardından oluşturulan en başarılı model olan xGBoost sınıflandırma modeli ile yapılan saatlik aydınlatma sınıfı tahminlerinin doğruluğu %96'nın üzerindedir. Gerçek veriler ile yapılan karşılaştırma sonucu görülmüştür ki makine öğrenmesi tahminlerine dayanan ARL yaklaşımının uygulanması halinde yıllık olarak 78,5 saat yetersiz aydınlatma yapılacaktır. Bu hatalar göze alınabilirse ortaya çıkacak enerji tasarrufu oranı ise yıl boyunca sabit olarak M2 aydınlatma sınıfında aydınlatma yapan bir sisteme göre yaklaşık olarak %29'dur. Bu yaklaşım uygulamaya alındığında yol kullanıcılarının güvenliğini ve görsel konforunu korumak amacıyla ani aydınlatma sınıfı değişikliklerinin önüne geçilmesi için tahmin edilen son on aydınlatma sınıfı değerinin mod değeri alınması kararlaştırılmıştır. Bu şekilde yapılan her tahmin ani olarak aydınlatma sınıfının değişmesine neden olmayacaktır. Formüle edilen stratejiler kuru hava koşulları dikkate alınarak geliştirilmiştir. İstanbul'da yıllık ortalama yağmurlu gün sayısı 117 olarak kabul edilmiştir. Yağmurlu havalarda sürücü görüşü ve konforunda olası azalma göz önüne alındığında, bu 117 gün için ARL senaryolarının askıya alınması ve yol aydınlatma sınıfının her zaman M2 aydınlatma sınıfı gerekliliklerine uygun olacağı kabul edilmiştir.

Bu çalışma, trafik akış hızları, araç hızları ve meteorolojik koşullarla uyumlu otomasyon stratejileri aracılığıyla mevcut yol aydınlatması sistemlerinin uyarlanabilir yol aydınlatması sistemlerine dönüştürülmesinin, yüksek oranda enerji tasarrufu sağlayabileceğini ortaya koymaktadır. Genel olarak bu çalışma, uyarlanabilir yol aydınlatma sistemlerinin geliştirilmesinde aydınlatma sınıfı tahmininin rolünün kapsamlı bir analizini sunmakta ve akıllı şehir altyapısındaki potansiyel pratik uygulamalarla, uyarlanabilir yol aydınlatma sistemlerinin enerji verimliliği ve sürüş güvenliği için optimize edilmesine yönelik bilgilerin geliştirilmesine katkıda bulunmaktadır. Uygulanan senaryo ve stratejilerin trafik güvenliğini ve yol kullanıcılarının görsel konfor koşullarını olumsuz etkilememesi için detaylı bir saha çalışmasının sürdürülmesi gerekmektedir. Standartlaştırılmış veri toplama ve örnekleme protokollerine duyulan ihtiyaç, büyük verilerin depolanması ve gizlilik sorunları, bu alanda gelecekteki tartışma konularından ve zorluklardan bazıları olacaktır.

1. INTRODUCTION

The lack of illumination in streets and roads has raised public concerns regarding safety and security. In situations where natural lighting is insufficient, lighting systems play a vital role, as they account for more than 19 percent of the total global electricity consumption [1]. These systems are among the largest consumers of electricity, accounting for 40 to 50 percent of the electricity used in urban societies. The worldwide count of street lights currently stands at 326 million, and this number is projected to rise coming years. Notably, street lights alone contribute to approximately 8% of the environmental pollution caused by greenhouse gas emissions [2] [3].

There exists no precise objective boundary distinguishing satisfactory from unsatisfactory levels of illuminance within urban areas. The feeling of insecurity is contingent upon various lighting factors, such as the mean level of illumination, the uniformity of illuminance distribution, and the color of light. Nevertheless, the specific surroundings and individual characteristics also play a role in determining the amount of light deemed as safe in an urban environment [4]. Enhancing the illumination on the street beyond a modest threshold of 5–10 lux has a negligible impact on the perception of safety [5]. Increased illumination on the road, nevertheless, leads to the emergence of light pollution. The elevated levels of public lighting exert an adverse environmental influence that affects not only humans but also animals and plants [6]. Additionally, the use of energy-saving LED lighting that emits a considerable amount of blue light has been associated with health issues related to the disorder of circadian rhythms [7].

To avoid making arbitrary decisions about the illumination level of urban streets, municipalities should rely on the Turkish road lighting standards TSE CEN/TR 13201, which provide a series of guidelines to adjust the lighting conditions based on the actual traffic conditions. According to the standards, each street in a city is assigned a lighting class, which is determined by various factors including time-dependent parameters such as traffic volume and traffic composition. The lighting design is then

implemented to cater to the most demanding traffic conditions that necessitate the highest level of illuminance on the road surface.

1.1 Purpose of Thesis

Implementing adaptive road lighting (ARL) systems is a strategy used to regulate road lighting. These systems are designed to adjust the lighting levels by utilizing traffic data gathered from roads and taking into account the surrounding environmental factors. It is crucial for an ARL system to prioritize the safety of drivers and pedestrians using the road while making these adjustments. In accordance with the standards, the luminance of the road can be lowered below the nominal level during peak hours, which are typically in the mornings and afternoons, as traffic volume decreases significantly late at night. The amount of energy saved as a result of implementing adaptive lighting depends on the temporal distribution of traffic volume.

The main drive behind this research is the insufficient number of ARL studies used in real road installations according to international standards in the literature, which will be examined in more detail in the next section. Although many ARL studies are commonly found in the form of simulations or prototypes, this study aims to provide guidance for sample applications, reports, and specification studies, distinguishing itself from the typical trend in the field. A determination was reached to develop novel models that would effectively decrease errors in lighting level controls for application on roads characterized by high traffic density and flow speed. Efforts have been undertaken to devise a methodology for gauging the energy conservation possibilities of street lighting solutions, which can be utilized in a thorough life cycle analysis to present a comprehensive overview of the economic and environmental implications of traffic-managed lighting control systems. In order to serve as a reference for future studies, the findings of diverse lighting strategies were unveiled and energy analyses were carried out.

1.2 Literature Review

In this section, studies suggesting that more energy efficiency in road lighting can be achieved with different control strategies, especially ARL systems, are compiled.

Various technologies are utilized in lighting systems, each differing in glare management, longevity, and specific characteristics. Recent efforts have focused on creating energy-efficient street lighting with appealing attributes. Research has indicated a shift towards high-efficiency LEDs over less effective traditional metal halides (MH) or high-pressure sodium (HPS) lights [8].

In addition to using energy more efficiently, LEDs can be a clear answer to existing street lighting systems because the amount of light flux emitted by the luminaire can be adjusted with various control methods. Additional reduction in energy consumption can be attained by implementing a logic system that regulates the intensity of LED lamps. This system would calculate appropriate luminance levels for specific areas or segments of the streets based on real-time traffic and weather data. By doing so, it would establish an on-demand lighting system, optimizing energy usage [9]. The primary cause of the increased energy consumption related to street lights can be attributed to the inefficient system, wherein the luminaries necessitate a substantial amount of energy. By carefully selecting the appropriate light source and employing advanced electronic control systems, outdoor lighting can achieve substantial energy efficiency. This can lead to reduced energy consumption and lower electricity costs, making outdoor lighting a sustainable and cost-effective solution.

Over the past years, there has been a notable global interest in smart lighting systems. Extensive research programs have been undertaken to showcase the capabilities and positive influence of smart technologies in optimizing the management of street lamps and road lights. These innovative technologies incorporate sensors, control algorithms, and wireless communications into street lamps, enabling them to function autonomously within the context of the Internet of Things (IoT). The smart lighting system comprises roads and streets that are lined with multifunctional smart lighting poles. These poles are equipped with a variety of devices that enable them to communicate with one another and share data with a remote management system.The core objectives of a smart lighting system are centered on enhancing the utilization of urban spaces, particularly in terms of energy conservation and cost-effectiveness.

The fundamental concept revolves around maintaining the lamps' luminous flux at the lowest acceptable level within a specific section of the street, in accordance with national/regional standards and safety regulations for both vehicular and pedestrian

traffic. The luminance level of the road should be adjusted in such a way that the minimum allowable level aligns with the established lighting standard.

Conventional lighting systems rely solely on daylight levels to determine the activation and deactivation of lights. In contrast, smart lighting systems offer the capability to incorporate sophisticated dimming techniques that adjust luminaire functionality based on factors such as pedestrian/vehicle presence, ambient light conditions, and time of day. Determining the consumption of a lighting system in an hour-based dimming process is made simple by establishing a correlation between the number of hours the system remains in a specific lighting state and the corresponding power requirement. This direct relationship facilitates the calculation of the system's consumption over a given time period. Findings of the analysis carried out by Pinto et al. indicate that a substantial reduction in the cost of control systems can greatly influence the feasibility of the system, resulting in payback periods of less than 5 years. This assessment takes into consideration the projected 40% decrease in control system costs that is anticipated to occur in the upcoming years [10].

Marino et al. developed a system in their research that utilizes an intelligent prediction algorithm and adaptive control system to save energy. The study was carried out on a 1.2 km long, two-lane road in Italy, where 53 LED luminaire points, three cameras for data collection and analysis, and sensors for monitoring weather conditions, vehicle detection, and light levels on street lighting poles were installed. Over a six-month period, traffic flow data was gathered, analyzed and used to predict traffic flow. Taking into consideration the established standards and weather conditions, adjustments were made to the dimming levels of light sources based on the lighting class values assigned to the road infrastructure. Rather than implementing a fixed lighting protocol , a dynamic lighting system was introduced using traffic flow prediction algorithms, leading to a 30% reduction in energy consumption compared to a non-automated system [11].

In an energy saving study conducted in Poland, it was argued that 4 luminaires in front of the vehicle should be open in order to maintain driver comfort while providing the necessary level of illumination on the road surface. Meanwhile, the first luminaire behind the vehicle and the 5th armature in front of the vehicle must be dimmed and on. Sensors were placed on each lighting pole to detect the presence of vehicles, and energy consumption and traffic data were monitored for a year. After the study, a

survey conducted by a group of road users concluded that in cases where no vehicle is detected, it would be more effective to slowly turn down the luminaires rather than turning them off completely [12].

A key aspect of the study that completed by Gagliardi et al., is the creation of a cost-effective lighting system that can regulate street light intensity based on the presence of traffic in a monitored street. The research aims to establish an IoT infrastructure where each lighting pole serves as a node in a network that can progressively enhance its coverage.The recommendation is to employ smart lighting poles that are composed of a local controller, a video camera, a computing unit for video processing, weather sensors, communication devices, and high-efficiency LED luminaires. Throughout the day, real-time traffic data is collected using video processing and then shared with the web application. At night, the LED luminaire dimming is adjusted based on the presence of vehicles or pedestrians in the area under surveillance. In cases where no vehicles or pedestrians are detected, the LED light intensity remains constant at the minimum level required by street lighting regulations. However, if a presence is detected, the LED light intensity is raised to the appropriate level for the area being monitored, taking into account the number of vehicles identified and the prevailing weather conditions. The evaluation of LED light intensity is directly linked to the presence of vehicles or pedestrians. In case of loss of connection or component damage, all intelligent functions are disabled and the system operates like a conventional lighting system. Within the lighting control circuit, the adjustment of lighting levels by utilizing information obtained from ambient brightness sensors and the weather station and it is designed to identify any abnormal behavior or malfunctions in street lights, promptly addressing such issues through the execution of the fault scenario. By adopting the 0–10 V DC analog lighting control protocol in accordance with the International Electrotechnical Commission Standards, it is possible for the luminaires to produce light levels of different intensities. The presence of vehicles and pedestrians was detected with video processing units to format traffic data. Compared to a non-smart LED lighting system in two different field environments, 48.81% and 70.65% energy saving ratios were calculated, respectively [13].

While the human body absorbs radio signals, vehicles reflect electromagnetic signals due to their metal composition. By analyzing how the energy of radio signals is

influenced by the characteristics of road users, it is possible to differentiate between vehicles and pedestrians. Moreover, variations in size between vehicles and pedestrians impact the level of energy attenuation in radio signals, allowing for the identification of road users. Jing et al. proposed monitoring the received signal strengths (RSS) from vehicles and pedestrians as they travel on roads to gather traffic data. The first step involves the collection of RSS data by the receivers. Subsequently, the RSS readings are employed to determine the type, speed, and location of road users. These detection results are then transmitted to the lighting control module, enabling the adjustment of the street luminaires' brightness through the utilization of the Pulse Width Modulation (PWM) signal [14].

The article introduces the concept of an IoT-enabled relay network for the purpose of designing a demand-based light intensity controlled highway lighting system. A key component of this system is a toll column that will remain illuminated continuously during the night, acting as an indicator for next lampposts that vehicles have entered the relevant lighting zone. The highway is segmented into sections, each section comprising a series of lampposts with the initial and final lampposts designated as anchor nodes. The anchor node is equipped similarly to the toll lamppost and serves the additional function of reporting any malfunctioning lamppost within its monitoring range to the control center. All the remaining lampposts possess relay capabilities, allowing them to activate their lights either by receiving information from the preceding lamppost or by utilizing their own sensing capabilities. If they receives notice of the existence of any vehicle information, it will transfer this information to the next lamppost. The presence of vehicles with light intensity and proximity sensors can be detected by the car sensing unit, which is linked to the processing unit, at the toll or first lamppost. It has been proposed that as drivers pass through different sections of the road, they will not perceive changes in lighting because the system automatically adjusts to the traffic flow. In the absence of passing vehicles at the toll lamppost, anchor and relay lampposts will dim to save energy. To maintain signal integrity as wireless signal strength diminishes over distance, multihop relay capability is integrated. Only a test environment was set up for the study and it has not been tested on any road [8].

The suggested system by Asif et al. does not require the addition of any sensors apart from the existing cameras that are already installed on the majority of streets for traffic

control and monitoring purposes. This implies that the implementation of the proposed system in the city would be relatively straightforward, as the cameras already present on highways for speed regulation can be repurposed without incurring any additional hardware installation expenses. Using the number of vehicles data obtained by image processing, they stated that an annual energy cost savings of up to 31.25% could be achieved in the road lighting systems that work with the fixed scenario they suggested, compared to LED lighting systems that always work at the same luminous flux [2].

In the study conducted by Balázs et al., the researchers examined the reliability of the traffic counting method by comparing manually recorded observations with automated machine vision data collected during both high and low traffic situations. In the first of the two different approaches they developed, the traffic volume was estimated with the data collected from the sensors and the light output of the luminaires was controlled with this data. The lighting system's lack of responsiveness to minute-scale traffic fluctuations is attributed to the hourly updates of the luminous flux of the luminaries. This relatively low responsiveness results in gradual transitions in road illumination levels, which, on one hand, ensures a smooth lighting experience but, on the other hand, restricts the energy-saving capabilities of the system. The second strategy utilizes a time controller to pre-program the dimming schedule of the luminaires and establish lighting control statistically. The distribution of traffic volume for the day is determined based on historical data, and the road illumination is adjusted to meet or exceed the minimum standard requirement. The comparison between the pre-programmed timer option and a 3-hour shut-off per night led to the conclusion that the former is significantly more energy efficient. This finding supports the notion that while turning off street lighting in cities may be seen as a temporary emergency measure, extensive research spanning over 60 years has consistently demonstrated that street dimming is a sustainable solution in the long run. Therefore, the claim that street dimming cannot be justified as a temporary emergency measure is substantiated. In instances of scheduled power shutdowns, high and low levels of illumination are linked to the maximum and minimum levels, respectively. Conversely, with pre-set dimming, the variance is usually restricted to one level above or below the required illuminance based on the prevailing traffic conditions. The most significant savings of 55% can be attained by implementing a responsive sensor network. In contrast, a pre-programmed dimming schedule utilizing long-term traffic data analysis yielded a 45%

reduction in energy consumption. On the other hand, turning off the lights completely for 3 hours per night only led to a 25% decrease in energy usage compared to maintaining constant full power operation from dusk until dawn [15].

The utilization of artificial intelligence applications for traffic flow predictions in road lighting has gained significant traction as a means to enhance energy savings. Apart from its application in traffic flow prediction and lighting control, this technology has also found utility in areas like traffic density detection and traffic light control. Researchers have employed two main approaches in their studies: the time series method, which involves analyzing historical traffic data using statistical calculations to forecast future traffic situations, and machine learning methods, which consider factors such as weather and road conditions alongside traffic data to predict future traffic scenarios. In the majority of these studies, the low error traffic data estimation required to ensure a safe road illumination level has been avoided. One of the reasons for this is that the processed datasets are not large enough to perform the necessary analysis.

In their study, Agremela et al.used 12 different types of data, such as occupancy and vehicle speed, collected from a 4-lane road in California. The dataset trained with Artificial Neural Networks (ANN) and Deep Neural Network (DNN) models, they achieved a mean absolute percentage error (MAPE) of 7.19% as the best result when estimating the number of vehicles that will pass through a lane throughout the hour [1].

On the other hand, although models that predict traffic data with high success rates have been produced, these models have not been used to control road lighting levels.

Abi-Char and Ashtaiwi collected data on weather conditions, speed, road type, and road conditions pertaining to traffic accidents in England over a period of 14 years. Their study aimed to determine the speed limit by analyzing 33 different inputs. To achieve this objective, they developed Artificial Neural Network, Decision Tree, and Linear Regression models, subsequently comparing the performance of each model. Non-numeric data, such as adverse weather conditions or poor road conditions, were transformed into numerical data through the Label Encoding technique. While the Decision Tree and Linear Regression models exhibited an accuracy rate of 96.83% and 96.88% respectively in the prediction process, the ANN model emerged as the most

suitable for facilitating adaptive updates to the speed limit due to its superior accuracy rate of 96.95% [16].

Kumar et al developed support vector regression (SVR) and ANN models for traffic volume prediction in Hyderabad city. For both models, data such as traffic speed, travel time and road width were used as input. Even though only one day of traffic data was processed, the SVR model yielded a MAPE result of less than 1%. However, the r-squared value, another model evaluation metric, remained at only 0.83. The result of the study was not linked to road lighting design [17].

The utilization of connected vehicle (CV) technology enables the exchange of information between two CVs as well as between any CV and the traffic infrastructure. The measurement of traffic density is considered to be spatial in nature rather than temporal. As a result, the temporal traffic occupancy measurements obtained from loop detectors cannot be utilized to estimate the traffic density for the entire link unless multiple loop detectors are installed, which incurs high costs. A more efficient approach to estimate the traffic density is to leverage CV technology, which allows for the real-time sharing of information such as the vehicle's location and speed anywhere within the link. Consequently, the objective of this research paper is to develop three data-driven methodologies for estimating the density of traffic flow on signalized approaches. These three data-driven approaches encompass an artificial neural network, a k-nearest neighbor approach, and a random forest (RF) model. An artificial neural network (ANN) method was employed to estimate the number of vehicles. The R value, which indicates the correlation between the model outputs and desired outputs, was approximately 0.86 for the training, validation, and testing datasets. A value nearing 1.0 signifies that the model outputs closely align with the desired outputs. To assess and compare the effectiveness of the proposed estimation approaches, the relative root mean square error (RRMSE) was utilized. The k-nearest neighbor approach yielded an optimal k value of 14, resulting in an RRMSE of 18.47%. The RRMSE value was near to 18% also for the RF model. With the ANN model, RRMSE values could be decreased as low as 9% [18].

Mean filtering estimation (MFE) model and long short-term memory (LSTM) neural network are integrated to enhance the accuracy of average vehicle speed estimation in a research from Türkiye. Both MFE and LSTM rely on speed data collected from roadside sensors in Istanbul during previous weeks that align with the same weekday

and time as the target time for prediction. This research presents a hybrid model for long-term traffic speed estimation that takes into account the intricate traffic patterns characteristic of a specific location. When the predictability of the flow becomes more straightforward, it may not be practical to employ a complex algorithm like LSTM. In such cases, a more effective approach is to simply calculate the averages from previous weeks. Conversely, the MFE algorithm begins to falter when the data patterns become more difficult to identify. In contrast, LSTM, being a robust algorithm, is capable of detecting more intricate patterns. Based on these findings, a hybrid architecture has been developed that leverages the strengths of both models. Experimental results demonstrate that combining these models holds promise for addressing the long-term traffic flow prediction problem, with an error rate of less than +/- 10 km/h [19].

1.3 Hypothesis

The cost of implementing full-fledged smart systems with sensor networks and individually controlled luminaires is a barrier for many municipalities and electric distribution companies, despite the potential for substantial operating cost savings. Although smart infrastructure provides added value through services like remote monitoring and predictive maintenance, the affordability of the complex IoT system remains a challenge for small communities. Removing the sensors from the control loop leads to a decrease in both initial capital outlay and ongoing operational expenses. However, this action will also lead to a loss of the system's ability to adjust to variations in the daily traffic patterns. One benefit of implementing a system where road lights are activated based on vehicle presence is the rapid response time and the potential for significant energy savings, despite a slight increase in initial investment. However, a drawback of this approach is the occurrence of alternating scenarios of full brightness and darkness or lights being turned off along the same stretch of road, leading to fluctuating light levels that may disrupt the surrounding environment.

The literature review shows that the positive aspects of all adaptive road lighting studies should be brought together. It is possible to create a safe and energy-efficient adaptive road lighting system with lighting class predictions made in accordance with TSE CEN/TR 13201 standards by training both real-time and historical data with machine learning models.

2. TERMS AND REGULATIONS USED IN ROAD LIGHTING

In order to enhance the visual performance and comfort of individuals utilizing road lighting, it is crucial to identify the lighting parameters that have a positive influence. This necessitates the definition of the fundamental lighting quantities that play a dominant role in the perception process of motorists, pedestrians, and residents, namely illuminance or luminance.

2.1 Luminance

The luminance of the road surface plays a crucial role in providing a background for potential objects on the road for motorized traffic. As a result, road surface luminance serves as the fundamental lighting parameter for road lighting in the context of motorized traffic. The visibility of a surface is achieved through the reflection of light and its subsequent entry into the observer's eye. The intensity of the visual perception is directly proportional to the amount of light that enters the eye. Consequently, the brightness of a road surface is contingent upon the quantity of light that is reflected towards the observer.

The visual experience of a road user is primarily determined by luminance rather than illuminance. This means that the complex arrangement of luminances in the road ahead directly affects the visual performance and comfort of the user. Various objects such as cars, bicycles, pedestrians, and obstacles have different reflection properties, leading to a wide range of luminances in the field of view. However, when it comes to dry road surfaces, the reflection properties are relatively consistent for motorists looking towards the road area approximately 50-150 meters ahead. As a result, the road-surface luminance can be reliably estimated based on a specific road-lighting system [20].

2.2 Contrast

An evaluation of a driver's visual abilities can be conducted through various performance measures. Key criteria include the ability to see stationary obstacles and moving objects (such as other vehicles and pedestrians), as well as the detection of relative motion. Merely detecting objects at the visibility threshold may not be sufficient for safe driving; optimal supra-threshold visibility enhances the likelihood of a driver reacting promptly.

In road lighting, where lighting levels are typically low, color vision tends to be ineffective. Visual detection primarily relies on luminance contrast, which is the difference in brightness between an object and its background. This is more crucial than differences in color perception. When an object appears darker than its background, it is perceived in silhouette with a negative contrast. Conversely, if the object is brighter than its background, it exhibits positive luminance contrast.

Road lighting systems are designed to enhance visibility by creating a contrast between dark objects and the illuminated road surface. The luminance level of the road surface directly impacts the number of objects that can be perceived as silhouettes [20].

2.3 Uniformity

In order to guarantee adequate visual performance on all areas of the road, it is important to maintain sufficiently high contrasts. This can be achieved by keeping the difference between the average and minimum road surface luminance within a reasonable range. One way to achieve this is by maintaining a high ratio of minimum-to-average road surface luminance. Overall uniformity, U_o, refers to the luminance ratio of L_{min} to L_{av} [20].

2.4 Glare

Two variations of glare exist: disability glare and discomfort glare. Disability glare, in particular, is the type of glare that has a detrimental impact on visual performance by interfering with the contrast and clarity of the road ahead. Headlights on vehicles traveling towards a driver on dark roads can significantly impair their ability to see clearly, impacting their visual performance [20].

2.5 Visual Comfort

The quality of road lighting is intricately connected to visual comfort, an aspect that is fundamentally subjective and can vary from person to person. Visual comfort plays a vital role, as insufficient lighting or poor lighting quality can lead to a range of negative outcomes. When visual comfort is not satisfactory, drivers are more likely to experience increased fatigue, which can result in diminished alertness and reduced visual performance. This decline in cognitive and visual capabilities can pose serious risks, ultimately compromising overall road safety.

The intensity of the lighting is crucial; overly bright lights can create discomfort and lead to glare, while inadequate lighting can hinder visibility. Furthermore, the uniformity of luminance across the road surface is essential. Ideally, road lighting should minimize harsh contrasts and create a consistent level of illumination, allowing drivers to perceive their surroundings clearly and thereby react more effectively to potential hazards. Additionally, the presence of glare—whether from oncoming headlights, overhead streetlights, or reflective surfaces—can greatly affect a driver's ability to see and make quick judgments. Glare not only distracts drivers but can also temporarily blind them, contributing to potential accidents and unsafe driving conditions.

LEDs have unique characteristics that can affect visual comfort due to their wider range of spectra compared to traditional light sources. Moreover, the small light-emitting surfaces of LEDs can produce more pronounced beams, potentially impacting visual comfort. It is important to note that most LED luminaires consist of multiple arrays of small LEDs, resulting in a non-uniform distribution of luminance on the light-emitting surface. This non-uniformity may also contribute to discomfort glare, further affecting visual comfort. An increase in the non-uniformity of the luminance distribution on the light-emitting surface of luminaires results in a corresponding rise in the perception of discomfort glare, regardless of whether the average luminance remains constant [20].

2.6 Road Lighting in Rainy Weather

During rainfall, a portion of the light emitted by a road-lighting system fails to reach the road due to two factors: absorption within raindrops and scattering by these

droplets in various directions. Nevertheless, the decrease in visibility caused by these phenomena, although inconvenient during the rain, is generally less severe compared to the reduced visibility resulting from a wet road surface. Even after the rain ceases, the road remains wet for a considerable period, significantly impacting visibility. This diminished visibility is a consequence of the altered reflective properties of the road surface.

During dry conditions, the luminance values of the bright patches can exceed ten times the values at the corresponding area. Consequently, the average luminance of the surface rises, but the overall uniformity diminishes. Although the heightened average road-surface luminance benefits the adaptation state of the driver's eyes, the reduced uniformity significantly hampers overall visual performance. The wet-weather quality of road lighting is primarily influenced by the nature of the road surface. However, the light distribution of the luminaires and the type of lighting arrangement also play a role, albeit to a lesser extent. Road surfaces with an open structure that effectively drain water maintain their diffuse reflective properties even when wet, resulting in a minimal decrease in the quality of road lighting during wet conditions [20].

2.7 European / Turkish Road Lighting Standards

Many national or regional standards for road lighting in different parts of the world are built upon the recommendations provided by International Commission on Illumination (CIE). To further demonstrate this, we can analyze the European Standard for Road lighting, established by the European Committee for Standardization (CEN). EN 13201-2 specifies the lighting values for each of the six lighting classes (M1–M6) used in the European standards, which align with the classes utilized by the CIE [21]. The appropriate lighting class for a particular scenario is outlined in CEN/TR 13201-1 and is determined by various factors such as:

- the complexity of the road geometry can be assessed based on the presence of divided carriageways and the frequency of intersections,
- traffic features such as speed, volume, composition, and presence of parked vehicles,
- ambient luminosity,
- the complexity associated with the navigational assignment

In order to ascertain the appropriate lighting class based on these factors, it is essential to select weighting values as outlined in Table 2.1 which is copied from the technical report CEN/TR 13201-1. The total of all weighting values, denoted as V_{ws}, dictates the lighting class M as [22]:

$$M = 6 - Vws \quad (2.1)$$

Table 2.1: Parameters for the selection of lighting class M.

Parameter	Options	Description		Weighting Value V_W
Design speed or speed limit	Very High	v ≥ 100 km/h		2
	High	70 < v < 100 km/ h		1
	Moderate	40 < v ≤ 70 km/h		-1
	Low	v ≤ 40 km/ h		-2
Traffic volume		Motorways, multilane routes	Two lane routes	
	High	> 65% of maximum capacity	> 45% of maximum capacity	1
	Moderate	35 % - 65 % of maximum capacity	15% - 45% of maximum capacity	0
	Low	< 35% of maximum capacity	< 15% of maximum capacity	-1
Traffic composition	Mixed with high percentage of non-motorised			2
	Mixed			1
	Motorised only			0
Separation of carriageway	No			1
	Yes			0
Junction density		Intersection/km	Interchanges, distance between bridges, km	
	High	> 3	< 3	1
	Moderate	≤ 3	≥ 3	0
Parked vehicles	Present			1
	Not present			0
Ambient luminosity	High	shopping windows, advertisement expressions, sport fields, station areas, storage areas		1
	Moderate	normal situation		0
	Low			-1
Navigational task	Very difficult			2
	Difficult			1
	Easy			0

The EN standard specifically addresses the concept of adaptive lighting, which has the ability to adjust to transient factors like traffic volume, traffic composition, weather conditions, and ambient lighting levels in order to achieve a notable decrease in energy usage. The lighting standards necessary for different traffic conditions, as outlined by the weighting values, may fluctuate throughout the evening and nighttime hours. It is emphasized in the standard that the utilization of weighting tables is crucial for this purpose. When the lighting system is configured to allow for dimming, significant

energy savings can be achieved. By adjusting the lighting levels to lower settings, substantial cost reductions can be realized with a flexible lighting setup. It is crucial to ensure that altering the lighting intensity does not compromise the road lighting requirements such as average luminance, overall and longitudinal uniformity. Therefore, turning off certain luminaries is not a viable option.

3. BÜYÜKDERE AVENUE TRAFFIC DATASET AND ROAD CHARACTERISTICS

The road section selected for this study is a major avenue which runs through multi districts on the European side of Istanbul. This section of the road consists of a total of six lanes, each is 3 meters wide. It has a 3.5 meters wide median. The luminaires were placed on 13-meter-high lighting poles with a distance of 40 meters between them. The poles are placed on the median and there are two luminaries on each pole. The speed limit is set at 70 km/h.

With a radar type sensor placed on the road, traffic flow rate and vehicle speed data, taken at 2-minute intervals for each lane on the road, have been recorded for a year and new data continues to be collected. Microwave radar technology is capable of detecting vehicles and pedestrians moving in various directions and speeds by analyzing the Doppler shift or phase difference. The signals obtained from these detections can then be utilized to regulate street lighting. In contrast to camera-based systems, microwave radars are not significantly impacted by low lighting conditions during nighttime. Additionally, microwave radars exhibit superior ambient temperature suppression capabilities compared to PIR sensors, thereby enhancing their effectiveness in detecting individuals on the road [14].

When determining the lighting class of the road, it is necessary to refer to the TSE CEN/TR 13201-1 technical report. As seen in the Table 3.1, total weighting value is counted as M2 with the decided options for each parameter. This will lead to the conclusion that M2 lighting class requirements should be provided for both lanes of the road under normal conditions. Since, in accordance with the standards, a maximum of 2 step changes can be made in M lighting class levels, in cases where dynamic parameter values change, there will be a possibility that the lighting performance criteria on the road will decrease to M3 and M4 lighting classes.

Table 3.1: Determination of Büyükdere Avenue lighting class.

Parameter	Options	Description		Weighting Value V_W	Case Study Road
Design speed or speed limit	Very High	v ≥ 100 km/h		2	
	High	70 < v < 100 km/ h		1	1
	Moderate	40 < v ≤ 70 km/h		-1	
	Low	v ≤ 40 km/ h		-2	
Traffic volume		Motorways, multilane routes	Two lane routes		
	High	> 65% of maximum capacity	> 45% of maximum capacity	1	1
	Moderate	35 % - 65 % of maximum capacity	15% - 45% of maximum capacity	0	
	Low	< 35% of maximum capacity	< 15% of maximum capacity	-1	
Traffic composition	Mixed with high percentage of non-motorised			2	
	Mixed			1	
	Motorised only			0	0
Separation of carriageway	No			1	
	Yes			0	0
Junction density		Intersection/km	Interchanges, distance between bridges, km		
	High	> 3	< 3	1	1
	Moderate	≤ 3	≥ 3	0	
Parked vehicles	Present			1	
	Not present			0	0
Ambient luminosity	High	shopping windows, advertisement expressions, sport fields, station areas, storage areas		1	1
	Moderate	normal situation		0	
	Low			-1	
Navigational task	Very difficult			2	
	Difficult			1	
	Easy			0	0
			Total weighting value V_{Ws}		4
			Lighting class		M2

Traffic flow rate is the total number of vehicles passing through a point in a certain period of time. The period is 2 minutes according to this road data set. CIE recommends using traffic flow rate data rather than traffic volume data for short periods such as minutes and hours. When calculating hourly traffic flow rates, the following two processes were applied for both directions, respectively: First, for each data point, the maximum of the 2-minute flow rate data of 3 lanes in the same direction was selected. Afterwards, 30 consecutive data collections were collected to obtain hourly traffic flow rate data. In this way, for each data point, traffic flow rate data for the next 1 hour was obtained. The maximum value of hourly traffic flow rate data collected in lighting hours on the road is 1402 vehicles/hour. This value was considered as the maximum value when determining the weight value of the traffic volume parameter when determining the lighting class. It is necessary to specify 35%

and 65% levels of the maximum traffic flow rate value since the road has multilanes. Table 3.2 shows these values and the corresponding weighting values.

Table 3.2: Weighting value equivalent of traffic flow rate levels.

Parameter	Options		Weighting Value
Traffic flow rate	High	$x > 911$	1
	Moderate	$491 \leq x \leq 911$	0
	Low	$x < 491$	-1

Since the road has always been used only by motor vehicles, traffic composition was considered a static parameter. Likewise, the fact that the ambient brightness on the road remained constant throughout the lighting hours led to the acceptance that this parameter was also static. Although traffic volume seems to be the only dynamic parameter when determining the lighting class of this road, average vehicle speeds are also accepted as a dynamic parameter in this thesis study. Even though the speed limit on the road is set as 70 km/h, it has been observed that the average speed is above this value during the hours when the road is empty. During busy hours, the speed is much lower than 70 km/h.

After this acceptance, it has been observed that accepting average vehicle speeds as a dynamic parameter causes sudden decreases or increases in the total weighting value. The reason for this is that, according to the lighting class determination table, when the speed exceeds 70 km/h, the relevant weighting value decreases from 1 to -1. This change will cause the current lighting class to instantly increase or decrease by 2 classes. Instant change of lighting class by 2 is a situation that should be prevented for the visual comfort of road users. Average vehicle speeds will affect drivers' driving characteristics. If the average speed is below 40 km/h, it indicates that the vehicle density on the road is high. Road users must be more careful, paying attention to the vehicles around them, and will therefore need more road lighting. In such cases, the very difficult option was preferred for the navigational task parameter. Since the increase in average vehicle speeds would indicate that the vehicle density on the road would decrease, it was assumed that the work of road users would become relatively easier, and when higher average speeds were observed, hard and easy options were also evaluated for the navigational task parameter. Table 3.3 summarizes the assumptions adopted and their impact on the total weighting value. In this way, sudden changes in the total weighting value due to speed changes were prevented.

Table 3.3: Dynamic parameter assumptions.

Average vehicle speed	Weighting Value	Navigational task	Weighting Value	Total Weighting Value
$v \geq 100$ km/h	2	Easy	0	2
$70 < v < 100$ km/ h	1	Easy	0	1
$40 < v \leq 70$ km/h	-1	Difficult	1	0
$v \leq 40$ km/ h	-2	Very difficult	2	0

After the assumptions were made, the matrix given in Table 3.4 was created with the dynamic parameters that would affect the lighting class on the studied road. According to the lighting class determination parameters in the TSE CEN/TR 13201-1 technical report, the default lighting class of the road was determined as M2. Since this class can be reduced by a maximum of 2, the minimum illumination class on the road is limited with M4.

Table 3.4: Lighting class determination matrix for studied road.

		Traffic flow rate (vehicle/hour)		
Average vehicle speed (km/hour)		x > 65% maximum capasity	35% < x < 65% maximum capasity	x < 35% maximum capasity
	70 < v < 100 km/hour	M2	M3	M4
	40 < v ≤ 70 km/hour	M3	M4	M4
	v ≤ 40 km/hour	M3	M4	M4

To develop a seasonal generalization aimed at estimating the total number of hours the road would be illuminated over the course of a year, a comprehensive analysis was undertaken. This involved examining the relevant astronomical data specific to the region where the road is situated. By scrutinizing patterns in sunrise and sunset times, the team was able to determine these times on one of the median days that characterizes each season, providing an equitable representation of variations in daylight across the year [23]. It was assumed that the lighting would remain on longer for sunrise and sunset times that did not coincide with a full or half hour. Table 3.5 shows the approximate hours at which the lighting on the road will remain on in each season. Based on this approach, it is calculated that the luminaires will remain on for 4419.5 hours throughout the year.

Table 3.5: Total lighting hours for the year.

Season	Total Days	Median Sunrise Time	Median Sunset Time	Lighting Hours for a Day	Lighting Hours for the Season
Winter	90	08:30	18:00	14.5	1305
Spring	92	06:30	19:30	11	1012
Summer	92	06:00	20:30	9.5	874
Fall	91	07:30	18:00	13.5	1228.5
Total Lighting Hours for the Year:					4419.5

Since the lighting class of the road is determined as M2 according to the standards, M2 lighting level performance requirements must be met in both directions for every hour of illumination throughout the year in a fixed scenario. The energy to be consumed in this fixed lighting scenario was simulated and calculated in Dialux. There will be 26 luminaires per kilometer in one direction on the road. Considering the two directions, 52 luminaires will be used to illuminate one km of road. The amount of power consumed by the luminaire to be used in proportion to the luminous flux it will emit is given in Table 3.6.

Table 3.6: Luminaire values.

Power (P)	Power factor	Luminous flux (lm)
20.35	0.666	2590
49.9	0.899	7556
77.3	0.95	11690
105.5	0.973	15600
134.7	0.984	19200
164.1	0.99	22500

Calculations made at Dialux have shown that in order to meet M2 lighting level performance requirements in both directions, all luminaires on the road must operate at 19200 lm luminous flux. Photometric results of the lighting simulation can be seen in Table 3.7.

Table 3.7: Photometric results for M2-M2 lighting simulation.

M2	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	1.5	0.65	0.84	8	0.92
Required values according to class	≥ 1.50	≥ 0.4	≥ 0.7	≤ 10	≥ 0.5

The calculation of the energy consumed for a year by a fixed lighting scenario is detailed in Table 3.8. In this particular scenario, there are 26 luminaires installed along each side of a designated 1 kilometer stretch. To quantify the energy usage, we evaluate the annual consumption, which is presented in megawatts (MW). This data specifically pertains to the lighting tailored for a two-way road that extends only 1 kilometer. In studying the yearly energy consumption, factors such as the power consumption of each luminaire, the hours of operation per day, and the number of operating days in a year are taken into account.

Table 3.8: Total power consumption for fixed lighting scenario (per km).

Lighting class	Total Hours for a Year	Number of luminaries	Number of directions	Power Consumption (Wh)	Annual Power Consumption (MWh)
M2-M2	4419.5	26	2	134.7	30.956

The monthly average number of rainy days for the region where the road is located obtained from the Turkish State Meteorological Service can be examined in Table 3.9 [24]. Seasonal totals are rounded to the nearest integer above. The number of rainy days is a data that should be noted, as rainfall and wet ground affect drivers' vision. For the safety of road users, the existing ARL system on the road should be paused on rainy days and M2 lighting class requirements should be met for both directions.

Table 3.9: Seasonal total rainy days.

	December	January	February	March	April	May
Average Number of Rainy Days	15.66	16.53	14.19	12.8	10.3	7.66
Seasonal Totals		46			31	
	June	July	August	September	October	November
Average Number of Rainy Days	5.6	3.56	3.64	5.56	9.56	11.49
Seasonal Totals		13			27	

When the above-mentioned assumptions are implemented together with the standards, the dynamic parameters will affect the total weighting values, thus the lighting class of the road will also become dynamic. It is possible to say that the road does not always have to meet M2 lighting level requirements in both directions. Table 3.10 shows the number of hours of lighting levels that would be sufficient to be applied on the road throughout the year. It may be necessary to provide different classes of lighting on

both sides of the road at the same time, so the lighting class is presented in groups of two. The total energy to be consumed for lighting according to actual data is also stated in the table. These obtained values will be used as a comparison criterion with the values to be executed in following ARL systems.

Table 3.10: Total power consumption for actual data (per km).

Lighting class	Total Hours for a Year	Power Consumption (kWh)	Total Power Consumption (MWh)
M2-M2	17	7.004	0.12
M2-M3	382.2	6.197	2.37
M2-M4	103.9	5.859	0.61
M3-M3	1266.5	4.508	5.71
M3-M4	567.2	4.025	2.28
M4-M4	2082.7	3.263	6.8
Total	4419.5		17.89
If M2-M2 lighting levels are applied on rainy days (117 total days)			22.08

During the hours when M2 lighting class should be provided in one direction and M3 in the other direction, the luminaires on the side of the direction where M2 lighting class should be provided should work with 21440 lm luminous flux, while the luminaires on the direction of which M3 lighting class should be provided should work with 12350 lm luminous flux. Photometric results of the lighting simulation can be seen in Table 3.11. Average luminance did not exceed 1.2 times the required value in either direction.

Table 3.11: Photometric results for M2-M3 lighting simulation.

M3	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	1.17	0.6	0.84	7	0.93
Required values according to class M2	≥ 1	≥ 0.4	≥ 0.6	≤ 15	≥ 0.5
Calculated values	1.5	0.68	0.81	7	0.9
Required values according to class	≥ 1.5	≥ 0.4	≥ 0.7	≤ 10	≥ 0.5

At the designated hours for M2 lighting class to be provided in one direction and M4 in the opposite direction, luminaires on the side requiring M2 lighting class should operate with a luminous flux of 22500 lm, whereas luminaires on the side requiring

M4 lighting class should operate with a luminous flux of 9400 lm. The photometric outcomes of the lighting simulation are illustrated in Table 3.12. While the minimum requirements were met in the direction that should be illuminated as M2, illuminating the other direction as M4, which is 2 classes lower, brought about a high illumination effect from the opposite direction. Although the luminaires to be used on the road that should be illuminated as M4 were operated with the lowest possible luminous flux, the average luminance target of 0.75 cd/m^2 was surpassed by a notable margin, 1.2 times greater than the stipulated requirement.

Table 3.12: Photometric results for M2-M4 lighting simulation.

M4	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	1.02	0.57	0.83	7	0.94
Required values according to class M2	≥ 0.75	≥ 0.4	≥ 0.6	≤ 15	≥ 0.5
Calculated values	1.5	0.69	0.81	7	0.9
Required values according to class	≥ 1.5	≥ 0.4	≥ 0.7	≤ 10	≥ 0.5

In order to meet M3 lighting level performance requirements in both directions, all luminaires on the road must operate at 13020 lm luminous flux. Photometric results of the lighting simulation can be seen in Table 3.13.

Table 3.13: Photometric results for M3-M3 lighting simulation.

M3	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	1.02	0.65	0.84	7	0.92
Required values according to class	≥ 1	≥ 0.4	≥ 0.6	≤ 15	≥ 0.5

When M3 lighting class is scheduled to be provided in one direction and M4 in the opposite direction, the luminaires on the side requiring M3 lighting class should operate with a luminous flux of 14310 lm, whereas the luminaires on the side necessitating M4 lighting class should operate with a luminous flux of 8969 lm. The photometric data from the lighting simulation is presented in Table 3.14. Average luminance did not exceed 1.2 times the required value in either direction.

Table 3.14: Photometric results for M3-M4 lighting simulation.

M4	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	0.82	0.61	0.84	7	0.93
Required values according to class	≥ 0.75	≥ 0.4	≥ 0.6	≤ 15	≥ 0.5
M3					
Calculated values	1.02	0.67	0.81	7	0.91
Required values according to class	≥ 1	≥ 0.4	≥ 0.6	≤ 10	≥ 0.5

To fulfill the M4 lighting level performance criteria in both directions, it is imperative that all luminaires on the road function at a luminous flux of 9550 lm. The photometric findings from the lighting simulation are illustrated in Table 3.15.

Table 3.15: Photometric results for M4-M4 lighting simulation.

M2	L_{av} [cd/m^2]	U_0	U_I	TI [%]	SR
Calculated values	0.75	0.65	0.84	7	0.92
Required values according to class	≥ 0.75	≥ 0.4	≥ 0.6	≤ 15	≥ 0.5

The decision to create adaptive road lighting systems with two different methods was a strategic one aimed at achieving a comprehensive understanding of how these systems perform in real-world scenarios. By testing the effectiveness of two distinct approaches, valuable insights can be gained into their respective strengths and weaknesses.

The first method involves a statistical approach. Traffic flow rate and vehicle speed averages were calculated for each season, and hour-based lighting class expectations were determined with lighting classes created according to seasonal traffic data averages.

For the second method, various machine learning models were produced after the dataset was adapted. It has been observed that among these models, the Extra Gradient Boosting Classification creates the fastest and most accurate lighting class predictions for the dataset.

4. RESULTS

4.1 Pre-programmed Statistical Approach

In this statistical approach, the very first action taken was to segment the dataset into two distinct categories: weekdays and holidays. This classification system was established primarily due to the inherent differences in traffic patterns exhibited on weekdays compared to weekends or designated holidays. During weekdays, standard commuter behaviors dominate, influenced by work hours and school schedules, leading to a more consistent and predictable flow of vehicles on the road. Conversely, weekends and holidays typically showcase a more diverse array of activities and travel behaviors resulting in fluctuating traffic volumes that can deviate markedly from typical weekdays. Thus, if one were to apply statistical methodologies uniformly across these two different types of days—treating weekdays and holidays as equivalent when analyzing the dataset—the likelihood of obtaining erroneous estimates regarding critical variables, such as the appropriate lighting class, would increase significantly. Inaccurate estimations could stem from not recognizing the unique characteristics of each traffic pattern, which could, in turn, lead to misguided decisions in resource allocation or infrastructure development.

Since an approach based on seasonal averages will be adopted for the data analysis, the original data set has been further divided into 4 separate seasons. This division resulted in the creation of 8 distinct data sets, with each data set specifically focusing on either weekdays or holidays for each season. This method allows for a more detailed and nuanced examination of the data, as it takes into account the varying patterns and trends that may be present in different seasons throughout the year. By breaking down the data in this way, researchers can gain a more comprehensive understanding of how various factors may impact the data across different times of the year. This approach not only helps to provide more accurate and reliable results but also enables a more thorough analysis of the data set as a whole.

All data sets were grouped according to the hour:minute information in the time column, allowing for the calculation of averages for each hour interval. By analyzing

these averages, we were able to generate data on the average traffic flow rate and average vehicle speed for every hour within the dataset. This method of grouping and calculation also enabled us to determine weekday and holiday average values separately for direction A and direction B, ultimately resulting in the creation of informative graphs displaying the trends for both directions. Overall, this meticulous approach to data analysis provided valuable insights into the traffic patterns and speeds on different days and times, helping to inform decision-making processes and improve traffic management strategies.

Approximately only the hours required for illumination were used when preparing the graphics. Vertical lines show the start and end times of illumination. The average traffic flow rate and average vehicle speed during lighting hours for weekdays in winter are plotted in the graph in Figure 4.1. Similarly, the average traffic flow rate and average vehicle speed during lighting hours for summer holidays are given in the graph in Figure 4.2. Average traffic flow rate and average vehicle speed graphs for all seasons and all directions are drawn for both weekdays and holidays and are given in Appendix A.

After average traffic flow data and average vehicle speed data were obtained, average weighting values were derived by taking into account the lighting class determination parameters and the assumptions mentioned in the previous section. The weighting values were derived based on factors such as traffic flow rate, average vehicle speed and navigational task. By adding up the weighting values obtained, average illumination class values were created for each hour:minute data. Since the basic lighting class of the road is determined as M2 in accordance with the standards, a restriction has been made to determine the lowest lighting class M4. The weekday and holiday average M lighting classes created for direction A and direction B resulted in the graphs. In order to avoid sudden changes in the lighting class, the class was changed not immediately, but after remaining at the same lighting class for 10 minutes. To achieve this, the mode value of the last 10 lighting classes was examined and the most recurring lighting class was decided to be the next. The weekday average M lighting classes for for winter are plotted in the graph in Figure 4.3. Similarly, the holiday average M lighting classes for summer are plotted in the graph in Figure 4.4.

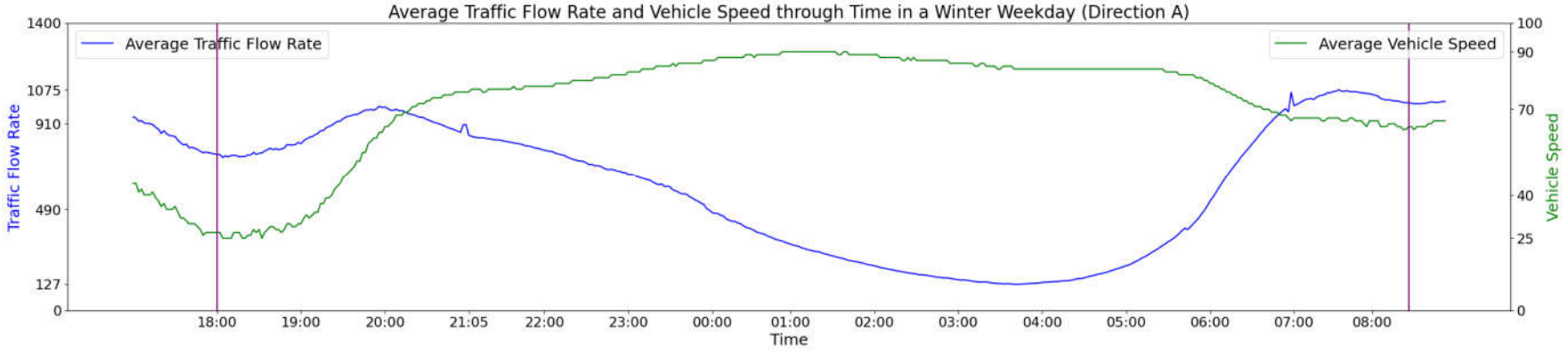

Figure 4.1: Average traffic flow rate and vehicle speed through time in a winter weekday (direction A).

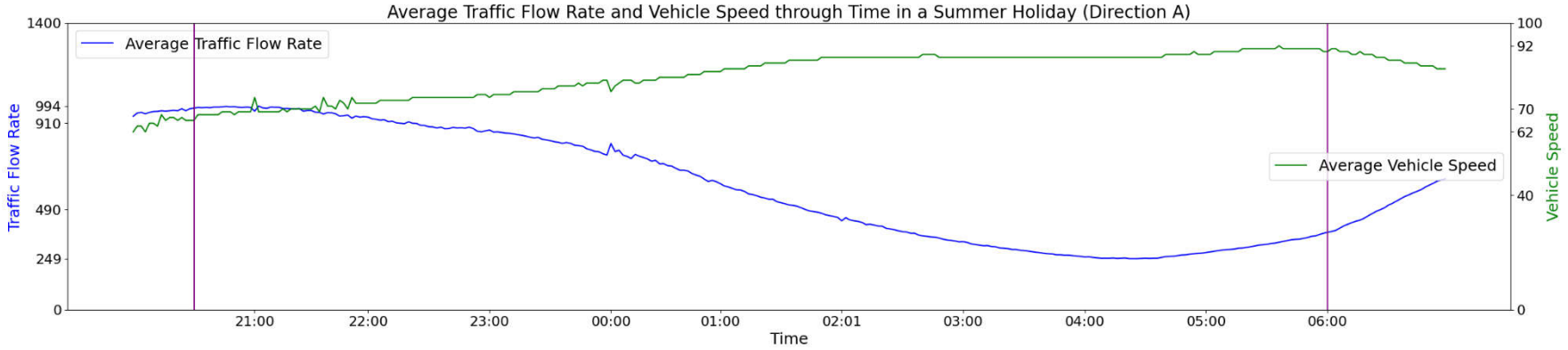

Figure 4.2: Average traffic flow rate and vehicle speed through time in a summer holiday (direction A).

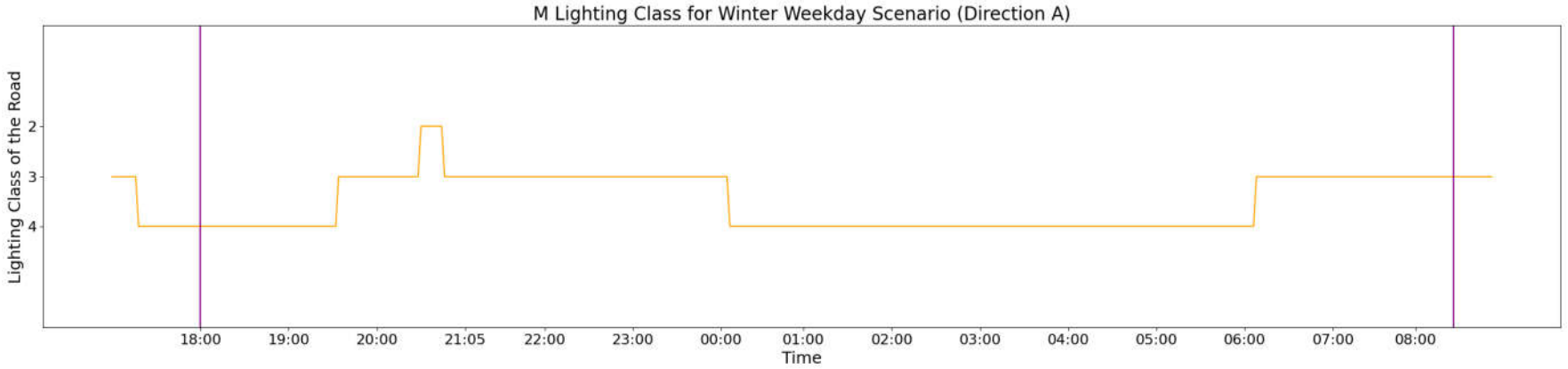

Figure 4.3: M lighting class for winter weekday scenario (direction A).

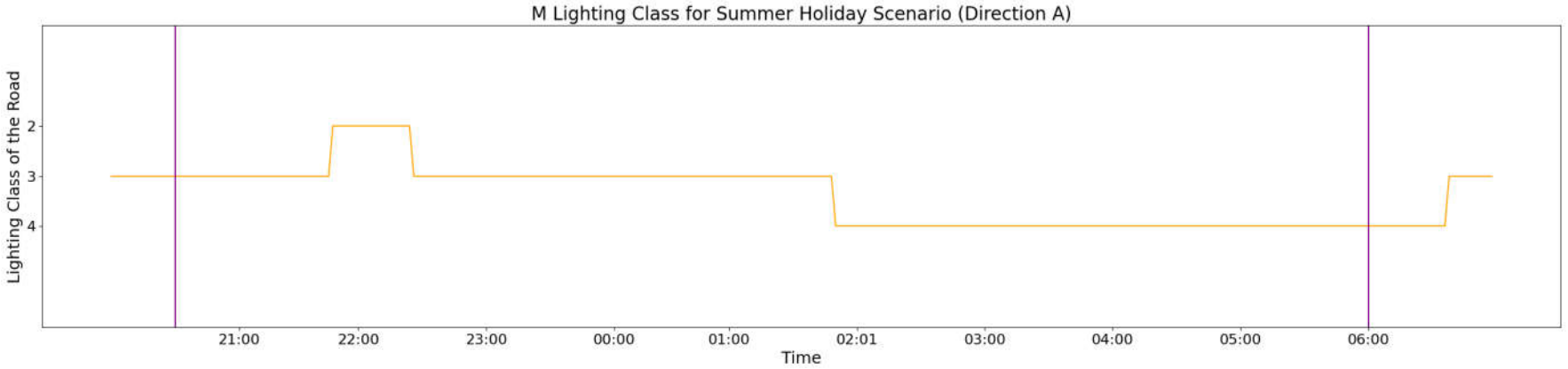

Figure 4.4: M lighting class for summer holiday scenario (direction A).

Since lighting in one direction will also affect the other direction, it is necessary to know which lighting class will be illuminated in both directions at the same time. For this reason, the lighting levels planned to be applied in two directions are drawn on a single graph. These graphs can also be examined in Appendix A. The lighting levels planned to be applied in two directions for winter weekdays are plotted in the graph in Figure 4.5. Similarly, the lighting levels planned to be applied in two directions for the summer holidays are plotted in the graph in Figure 4.6. The lighting levels planned to be applied in two directions for all seasons are drawn for both weekdays and holidays and are given in Appendix A.

Apart from graphics, the results are also expressed in numerical values. Table 4.1 shows the hours to be spent on lighting levels required for a year when both directions are evaluated together.

Table 4.1: Total power consumption for statistical ARL approach.

Lighting class	Total Hours for a Year	Power(kWh)	Total Power (MWh)
M2-M2	39.7	7.004	0.28
M2-M3	317.8	6.197	1.97
M2-M4	66.8	5.859	0.39
M3-M3	1371.7	4.508	6.18
M3-M4	524.4	4.025	2.11
M4-M4	2099.1	3.263	6.85
Total	4419.5		17.78
If M2-M2 lighting levels are applied on rainy days (117 total days)			22

It has been concluded that in the seasonal average lighting classes approach, lighting will not need to be applied as M2 for both directions at the same time. However, on rainy days, the statistical ARL system should be abandoned and lighting should be provided in both directions according to the M2 class, which is the default lighting level of the road. Therefore, when calculating the total energy consumption for the statistical ARL approach, the necessity of constant M2-M2 lighting on rainy days should also be taken into consideration.

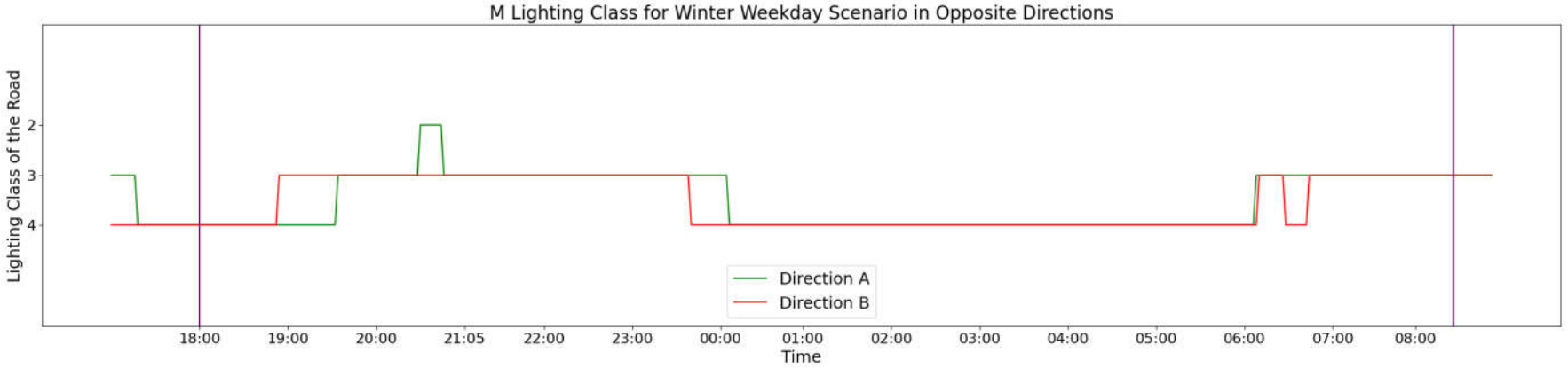

Figure 4.5: M lighting class for winter weekday scenario in opposite directions.

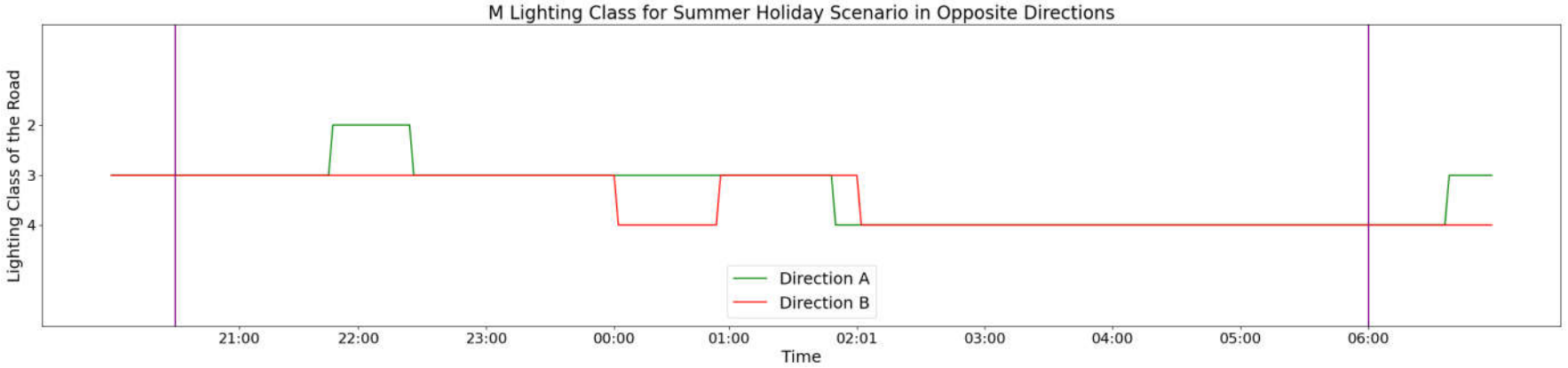

Figure 4.6: M lighting class for summer holiday scenario in opposite directions.

Apart from the total energy consumption, the error of the statistical ARL approach also needs to be measured. Since M lighting class values are derived for the real hourly traffic flow rate and vehicle speed values in the dataset, it is possible to measure the error rate of the actual values and the M lighting class values derived in the statistical ARL approach. The calculated total amount of incorrect illumination hours and error rates on a seasonal and total basis are given in Table 4.2.

Table 4.2: Time with incorrect lighting for statistical ARL approach.

	Winter	Spring	Summer	Fall	Totals
Lighting Hours for the Season	1305	1012	874	1228.5	4419.5
Hours with lighting fault	196.1	145.5	140.1	202.5	684.2
Insufficient lighting (h)	101.8	94.5	46.4	95.1	337.8
Error rate - Weekdays (A)	11 %	14 %	12.9 %	13.6 %	15.5 %
Error rate - Weekdays (B)	13.6 %	7.4 %	18.2 %	15.8 %	
Error rate - Holidays (A)	20.9 %	19 %	16.7 %	23.9 %	
Error rate - Holidays (B)	23 %	24.1 %	17.5 %	16.9 %	

In addition to the total error, the hours when lighting is insufficient are also stated. When the lighting is excessive, the amount of energy saved will only decrease, while driving comfort and safety will not be provided at a sufficient level during the hours when the lighting is insufficient.

In order to visualize the errors made in the statistical ARL approach, the winter weekday lighting scenario was compared with the required illumination level M on a randomly selected day such as 17th of January. The resulting graph is given in Figure 4.7. Similarly, the summer holiday lighting scenario was compared with the required lighting level M on 9th of July. The resulting graph is given in Figure 4.8. All comparisons with randomly selected days in two directions for all seasons are drawn for both weekdays and holidays and are given in Appendix A.

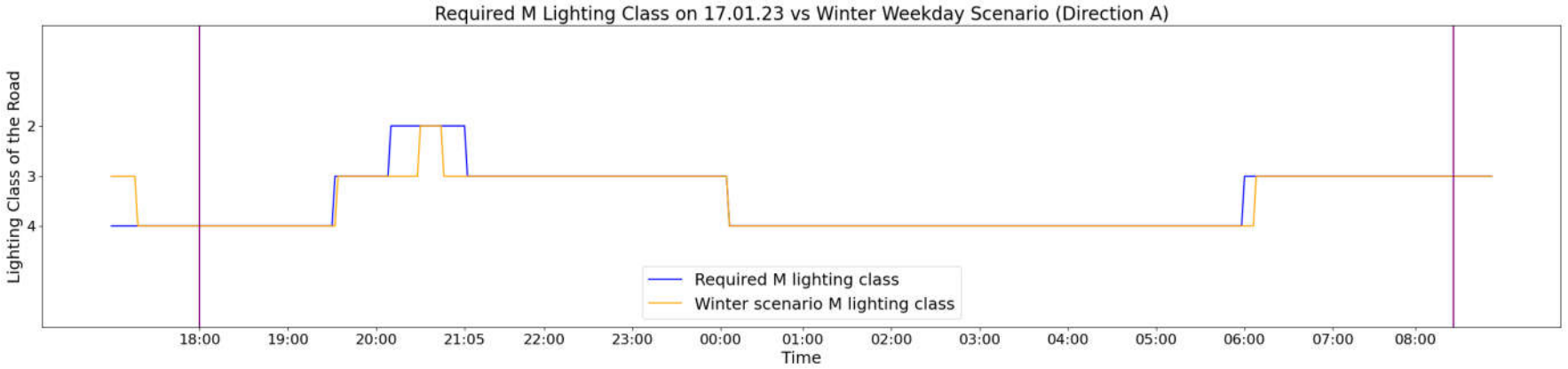

Figure 4.7: Required M lighting class on 17.01.2023 compared to winter weekday scenario (direction A).

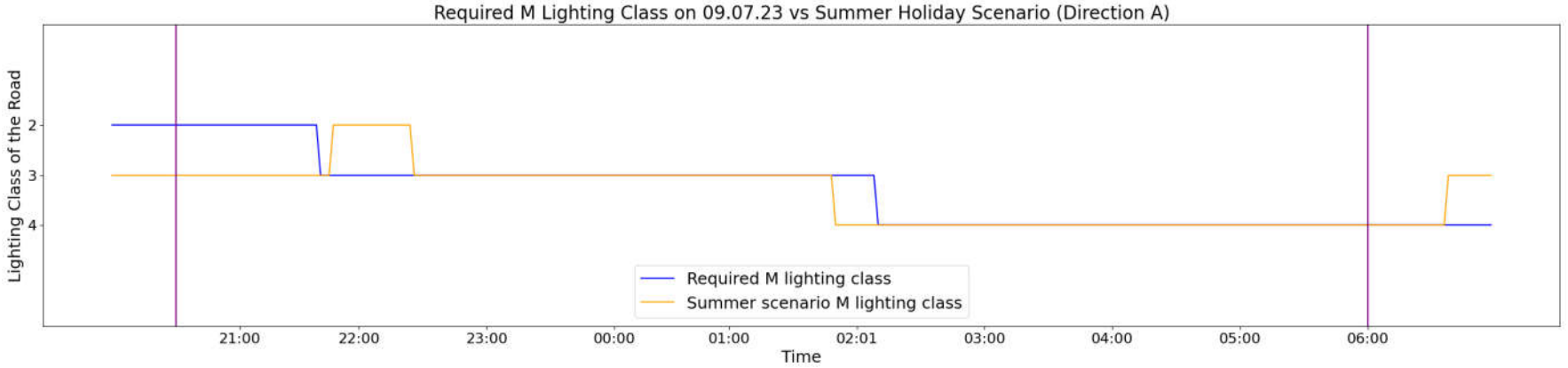

Figure 4.8: Required M lighting class on 09.07.2023 compared to summer holiday scenario (direction A).

4.2 Machine Learning Based Approach

In order to create a machine learning (ML) based ARL system, the dataset must first be preprocessed to make it suitable for training ML models. This involves cleaning and transforming the data to extract useful insights. One important step in this process is selecting the columns that will serve as input for the ML models. These columns should contain relevant information that can be used to make accurate predictions or classifications. This may involve combining or aggregating columns, as well as removing irrelevant or redundant information. Once the dataset is prepared, ML models can be trained using algorithms such as regression and classification. These models can then be used to make predictions or classifications based on new data.

The month, day, hour and minute information in the time column was divided into two columns to be used as input. A column has been created that specifies the day of the week as a numerical value. A column has been created for workdays. If the data in the relevant row belonged to a business day, the value in the column was accepted as 1, indicating that it was a typical workday. Conversely, if it was not a business day, such as a weekend or holiday, the value was marked as 0. This distinction helped to categorize and analyze the data based on the corresponding time frame. A similar approach was taken for school days. If the data fell on a day when school was in session, the corresponding value in the column was denoted as 1. This allowed for a clear differentiation between days when educational activities took place and days when they did not. By applying this systematic method, the dataset could be effectively organized and studied based on specific criteria.

Actual traffic flow rate data and actual vehicle speed data were also specified in one column in order to create a benchmark against the estimated values. It was decided that samples from instantly collected data should be used so that the ML models to be created can more easily adapt to sudden changes in traffic flow rate and vehicle speed data. For this purpose, two columns were created to sample the last 5 and the last 10 data for both traffic flow rate and vehicle speed data. In the columns where the last 5 values are sampled, the averages of the last 5 traffic flow rate and vehicle speed data collected from the road are given. In other words, these two columns are the average of the last 10 minutes of traffic data. Similarly, the two columns where the last 10

traffic flow rate and vehicle speed data are sampled are the average of the data collected from the road for the last 20 minutes.

Again, in order to use it for comparison purposes when determining the accuracy rate of the models, weighting values were derived from the actual traffic data compiled before and actual M lighting class values were reached. According to the standards, the road's default lighting class has been identified as M2. However, in order to establish the lowest lighting class, a restriction has been imposed, resulting in the determination of M4.

Since it would be pointless to train ML models with data collected during daylight hours, the dataset was finally filtered to include only lighting hours.

First of all, hourly traffic flow rate and hourly average vehicle speed data were tried to be estimated based on direction. Regression models such as support vector machines(SVR), gradient boosting, random forest, as well as models such as artificial neural networks and long short term memory were utilized to predict traffic data. With the prediction results, first the weighting values and then the estimated M illumination classes were produced. The same models were then used to predict the lighting class M as a numerical value instead of predicting traffic data.

To evaluate the performance of the models, metrics such as mean squared error, root mean squared error, R2 score, mean absolute error and mean absolute percentage error were examined. Satisfactory error rates could not be reached with the SVR model. Although ANN and LSTM models managed to make more precise predictions, they were eliminated because they could be slow to keep up with the dynamics of road lighting. Because they were more complex, it took a long time to produce prediction outputs for these models. As a result of these examinations, random forest regression and extra gradient boosting regression were the models that most successfully and quickly predicted the lighting classes for both directions of the road among the regression models. However, when the overfit status of the models was examined, it was seen that the models formed when the dataset was trained with random forest showed overfit properties. To understand this, the training data predictions were looked at and a large difference was observed between the training set error and the test set error in the random forest model. For this reason, random forest regression models were also eliminated and it was decided to continue with extra gradient

boosting models. Additionally, extra boost gradient models produce much faster predictions than random forest models.

Since there were 3 illumination classes that were likely to be predicted as M2, M3 and M4, it was decided to convert the model into a classification model. For this reason, an XGBoost classification model was created with the parameters determined so that the number of estimators used when producing the XGBoost regression model was 50 and the maximum depth was 9. The total energy consumption data of an ARL system to be created with the estimated M lighting classes is calculated in Table 4.3.

Table 4.3: Total power consumption for ML based approach.

Lighting class	Total Hours for a Year	Power(kWh)	Total Power (MWh)
M2-M2	5.9	7.004	0.04
M2-M3	385.3	6.197	2.39
M2-M4	102.3	5.859	0.6
M3-M3	1305.8	4.508	5.89
M3-M4	540.7	4.025	2.18
M4-M4	2067.5	3.263	6.75
Total	4419.5		17.85
If M2-M2 lighting levels are applied on rainy days (117 total days)			22.05

The accuracy scores of the M illumination classes predicted by this model for both directions are given in percentage terms in Table 4.4. In addition, as in the statistical-based ARL, the total incorrect illumination time and the total insufficient illumination time are tabulated in hours on an annual basis.

Table 4.4: Incorrect lighting hours and accuracy scores for ML based approach.

	Direction A	Direction B
Total lighting hours for a year	4419.5	
Accuracy score	96.3 %	96.1 %
Total incorrect lighting time for a year (h)	163	174
Total insufficient lighting time for a year (h)	81	76

Table 4.5 shows the classification matrix results for both directions. The True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) values obtained from these classification matrices are also summarized in the Table 4.6.

Table 4.5: Classification matrix for both directions.

Direction A		Predicted		
		M2	M3	M4
Actual	M2	2281	248	1
	M3	250	8451	163
	M4	5	164	10978
Direction B		**Predicted**		
		M2	M3	M4
Actual	M2	117	38	0
	M3	16	8659	352
	M4	0	483	12876

Table 4.6: TP, FP, TN and FN values.

Direction A				
Class	TP	FP	TN	FN
M2	2281	255	19429	249
M3	8451	412	13259	413
M4	10978	164	10732	169
Direction B				
Class	TP	FP	TN	FN
M2	117	16	21535	38
M3	8659	521	12993	32268
M4	12876	352	8776	483

It is important to note that while accuracy is a key performance metric for classification models, it should not be the only factor considered when evaluating the effectiveness of a model. There are other metrics that can provide valuable insights into the model's performance and help in making informed decisions. One of them is precision. It shows how many of the examples the model classifies as positive are actually positive. The metric that shows how many true positive samples are detected correctly is called recall or sensitivity. F1-Score is the harmonic average of precision and recall values. Since we have a multi-class target variable, the macro average was used when calculating performance metrics. In this way, each class has equal weight and the performance of smaller classes is reflected in the metrics. Balanced accuracy is derived by taking the arithmetic mean of sensitivity and specificity. This metric proves

valuable when dealing with imbalanced data, where one of the target classes is observed at a significantly higher frequency than the other. All the performance metrics mentioned are given in Table 4.7.

Table 4.7: Other performance metrics for ML based approach.

	Direction A	Dirrection B
Precision	0.946	0.932
Recall (Sensitivity)	0.947	0.893
F1-Score	0.946	0.911
Balanced Accuracy	0.947	0.893

In order to visually compare the M lighting class predictions with the required M lighting classes, a randomly selected weekday and a holiday are given as graphs in Figure 4.9 and Figure 4.10, respectively.

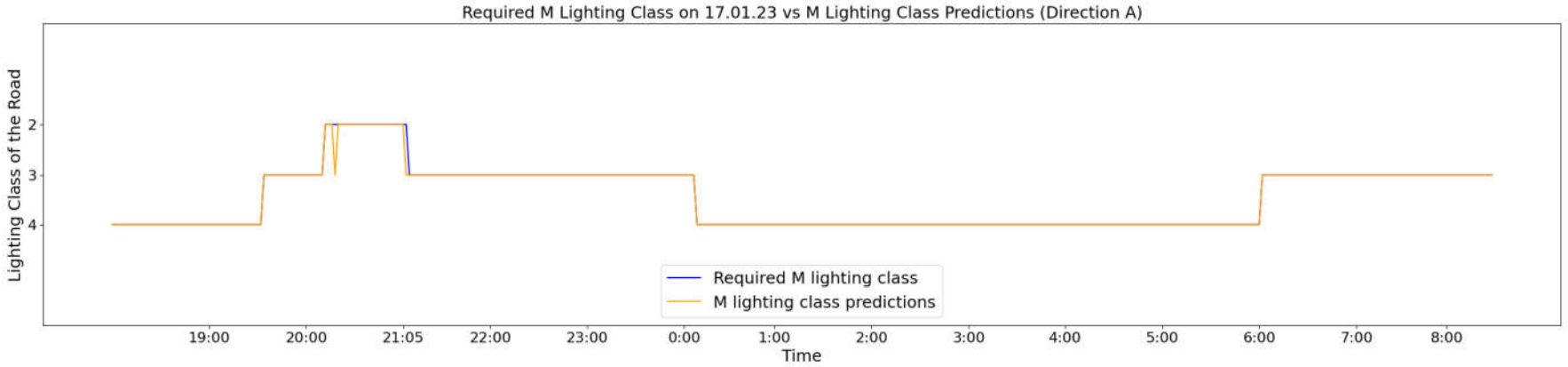

Figure 4.9: Required M lighting class on 17.01.2023 compared to M lighting class predictions (direction A).

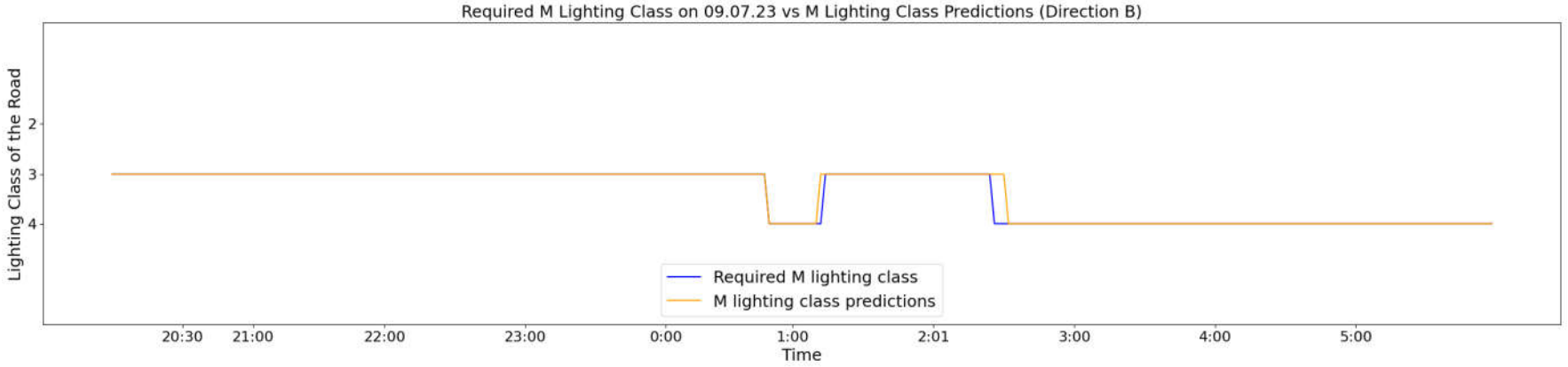

Figure 4.10: Required M lighting class on 09.07.2023 compared to M lighting class predictions (direction B).

5. CONCLUSION AND FUTURE WORK

The case study illustrates that adaptive road lighting has the potential to serve as a feasible substitute for conventional fixed road lighting. The integration of dynamic light control leads to substantial reductions in electricity consumption while maintaining road safety and public security. Rather than illuminating the roads at the same lighting class throughout the year, it will be possible to provide illumination to meet the needs of the road with ARL systems instantly.

As can be seen in Table 5.1, it is possible to achieve energy savings of nearly 30% with the current sensor investment with an ML-based ARL. Same amount of savings can be achieved with the pre-programmed statistical approach, but since the error rate is 4 times that of ML based ARL, it would not be right to choose this method. Although the hours when excessive lighting is used do not cause any problems other than excessive energy consumption, hours when the lighting is insufficient due to model errors can make the experience of road users difficult and reduce driving safety. For this reason, it is necessary to make as accurate predictions as possible when estimating the lighting class.

Table 5.1: Comparison of lighting systems

	Traditional fixed lighting	Pre-programmed, statistical ARL	Dynamic, ML based ARL	Actual data
Total consumed power (MW/year)	30.96	22	22.05	22.08
Energy saving	-	28.9 %	28.8 %	28.7 %
Energy saving (w/o rainy days)	-	42.6 %	42.3 %	42.2 %
Approximate rate of error	-	15.5 %	3.8 %	-

In addition to the energy savings and low error rates, the chosen model, the xGBoost classification model, is also capable of producing lighting class prediction outputs within a few seconds. It has a structure that can quickly adapt to sudden changes in traffic data such as traffic flow rate and vehicle speeds. In case of events, accidents

during lighting hours around the road that may affect the characteristics of the road and therefore traffic data, the selected machine learning model will provide much more accurate results than any statistical model.

The energy savings per km given in the table guarantee that ARL systems will provide huge savings when adapted to kilometers of road lighting. The most important situation that reduces energy saving is the complete disabling of ARL systems on rainy days due to the inadequacy of the existing mechanism. If the dryness of the asphalt on the road is detected by image processing or sensors and ARL is activated again as soon as possible, rather than leaving ARL systems disabled for all rainy days, energy saving rates could reach higher levels.

On the one hand, the dataset continues to expand as new data continues to be collected along the way. This expansion in the dataset will further increase the success of the trained artificial intelligence models. In this way, hours of incorrect illumination every day will be eliminated and the trained model's reaction to sudden changes in traffic data will be more accurate. Based on the available data, the M2 lighting class requires fewer hours of illumination compared to other classes, indicating that the prediction algorithms of the model are not adequately prepared for this particular class. Estimating lighting classes at lower during the designated M2 lighting hours may lead to insufficient road lighting. Nevertheless, with the expansion of the dataset, the prediction algorithm of the model will likely become more adept at recognizing and addressing this issue.

When the created ARL system is implemented on the pilot road, it is planned that the lighting class will not be changed for periods shorter than 20 minutes. In this way, incorrect lighting class predictions between consecutive minutes produced by the model as a correct prediction will be eliminated. The primary objective of this application is to ensure the driving comfort and safety of road users, while simultaneously decreasing the overall error rate of the model. All of this will enable the integration of a reliable, robust, energy-efficient and truly adaptive road lighting system.

In addition to the lighting class estimation algorithms developed in this project, traffic flow rate and vehicle speed estimation algorithms can serve as examples for studies in many other disciplines. While solutions to traffic jam problems in big cities can be

produced by analyzing and predicting traffic flow rate data, studies to prevent accidents can be carried out by analyzing and predicting vehicle speed data. The analyzing methods of traffic data used in this study and the widespread use of machine learning models trained with traffic data may shed light on studies from many different disciplines.

In this study, a cost analysis was not carried out. Given the significance of road lighting installations in public expenditures and the advancement in energy conservation, it is crucial to offer cost-effective solutions for project implementation. To achieve this goal, it is essential to employ cost analysis methods that take into account all relevant factor parameters. Furthermore, the energy saving rates presented in the research findings were formulated under the presumption that the respective road is presently illuminated with LED luminaries. Example roads with outdated lighting systems can also be incorporated in a cost evaluation investigation.

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APPENDICES

APPENDIX A: Graphs

APPENDIX A

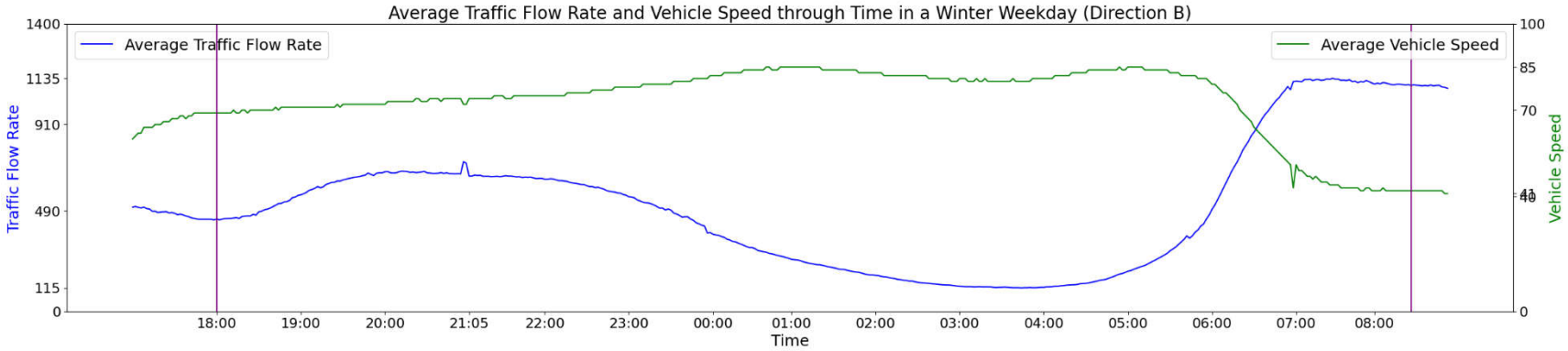

Figure A.1: Average traffic flow rate and vehicle speed through time in a winter weekday (direction B).

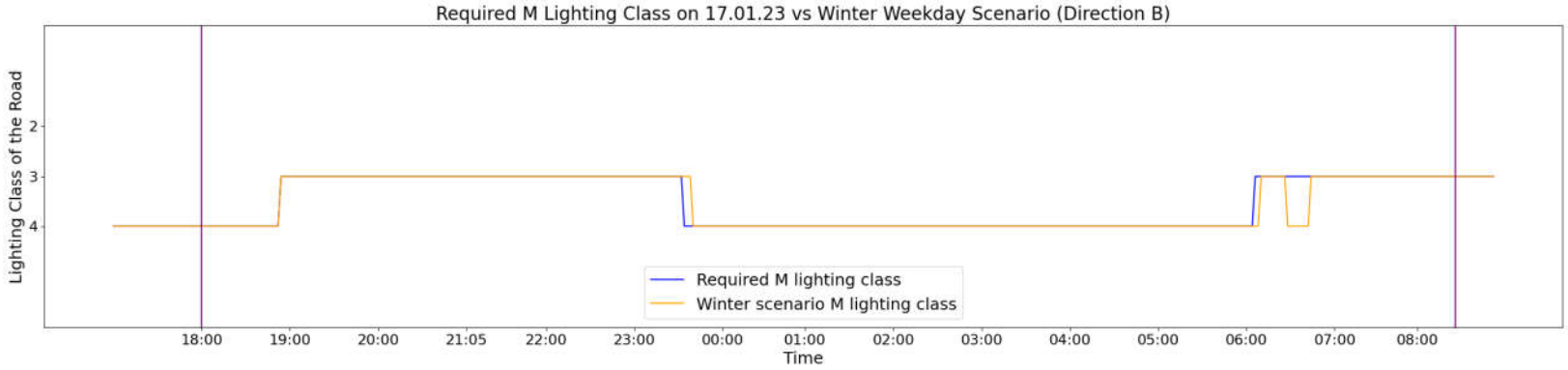

Figure A.2: Required M lighting class on 17.01.2023 compared to winter weekday scenario (direction B).

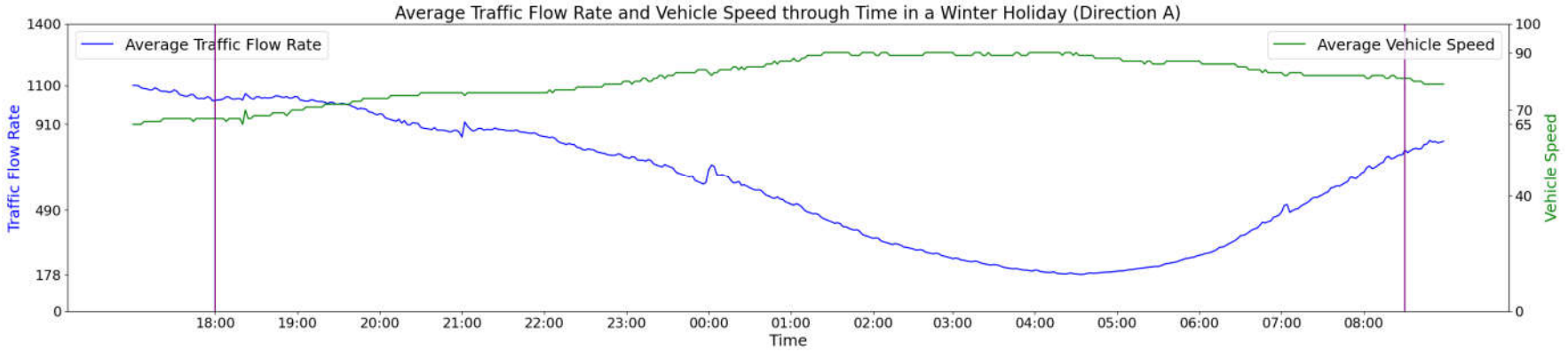

Figure A.3: Average traffic flow rate and vehicle speed through time in a winter holiday (direction A).

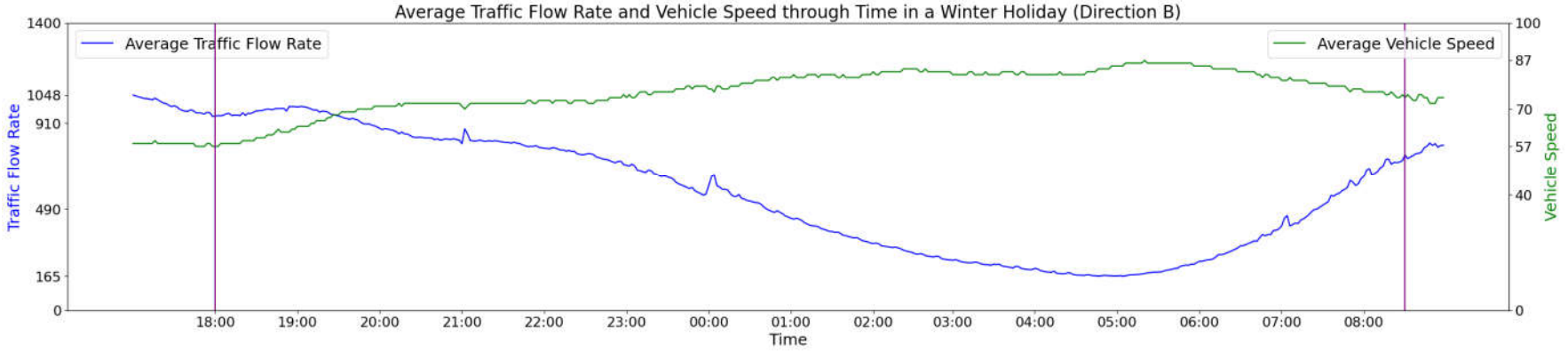

Figure A.4: Average traffic flow rate and vehicle speed through time in a winter holiday (direction B).

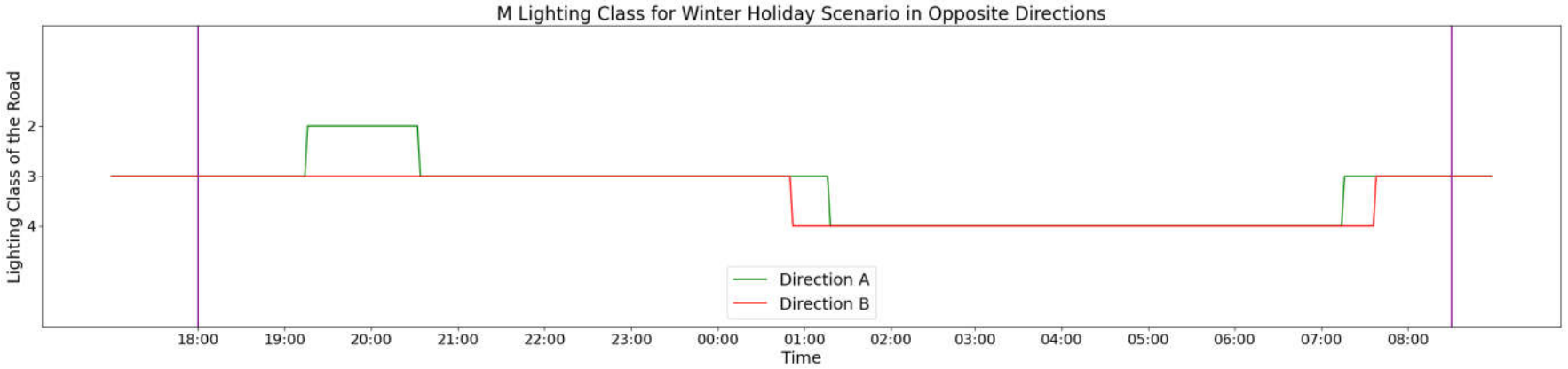

Figure A.5: M lighting class for winter holiday scenario in opposite directions.

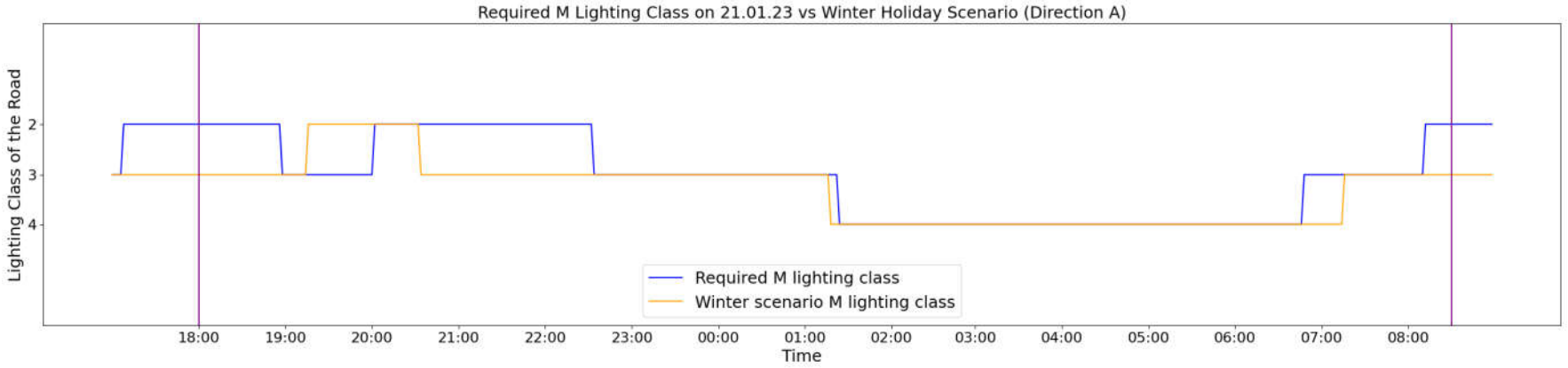

Figure A.6: Required M lighting class on 21.01.2023 compared to winter holiday scenario (direction A).

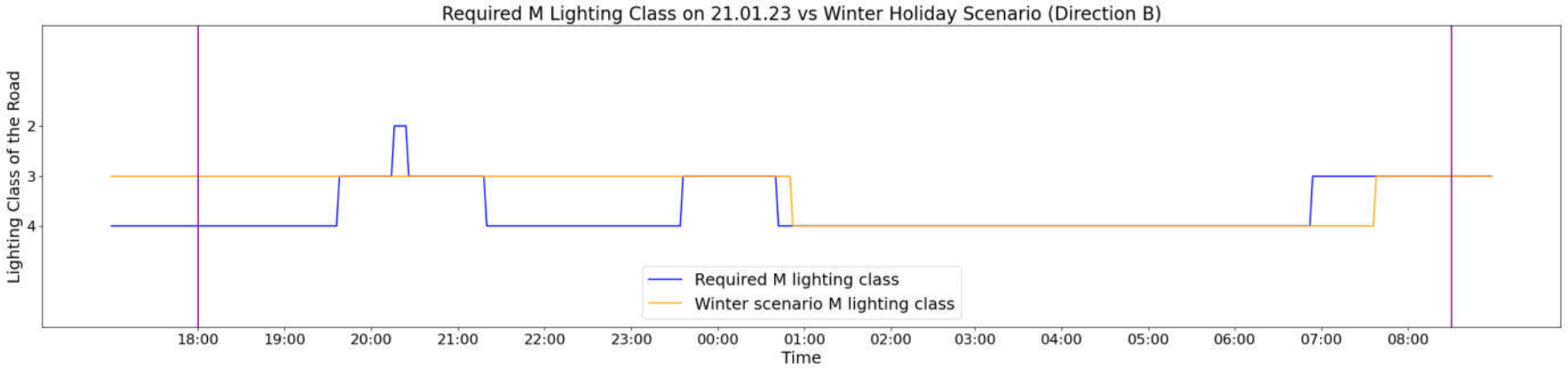

Figure A.7: Required M lighting class on 21.01.2023 compared to winter holiday scenario (direction B).

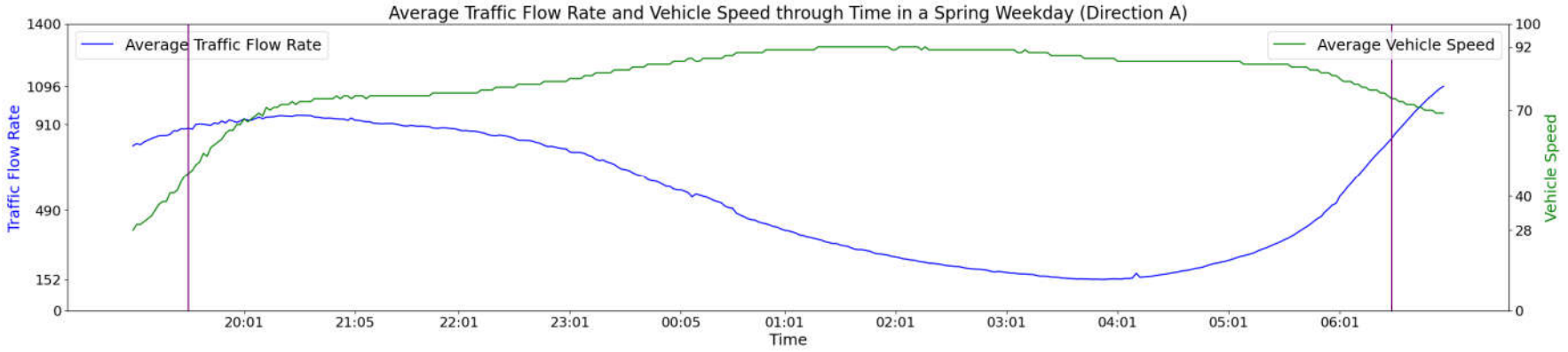

Figure A.8: Average traffic flow rate and vehicle speed through time in a spring weekday (direction A).

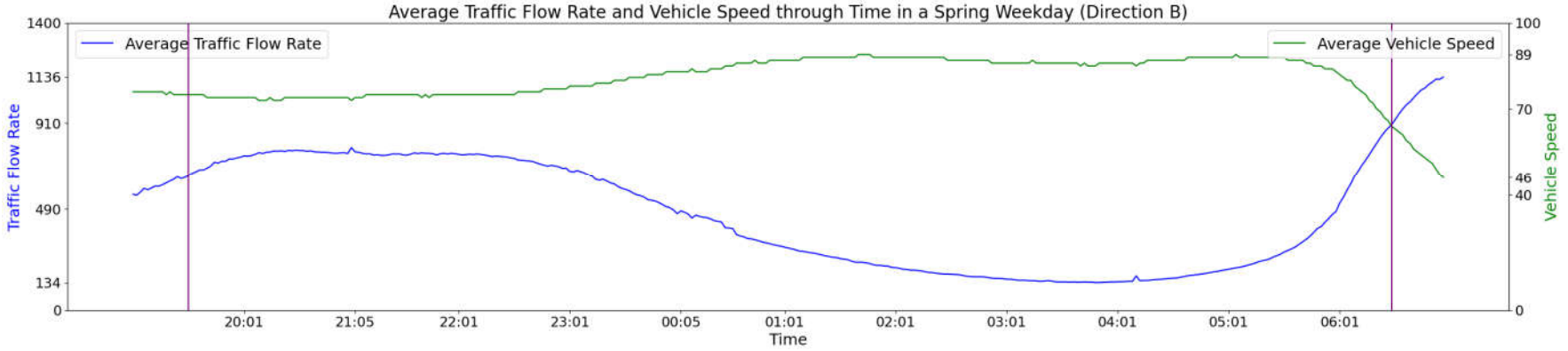

Figure A.9: Average traffic flow rate and vehicle speed through time in a spring weekday (direction B).

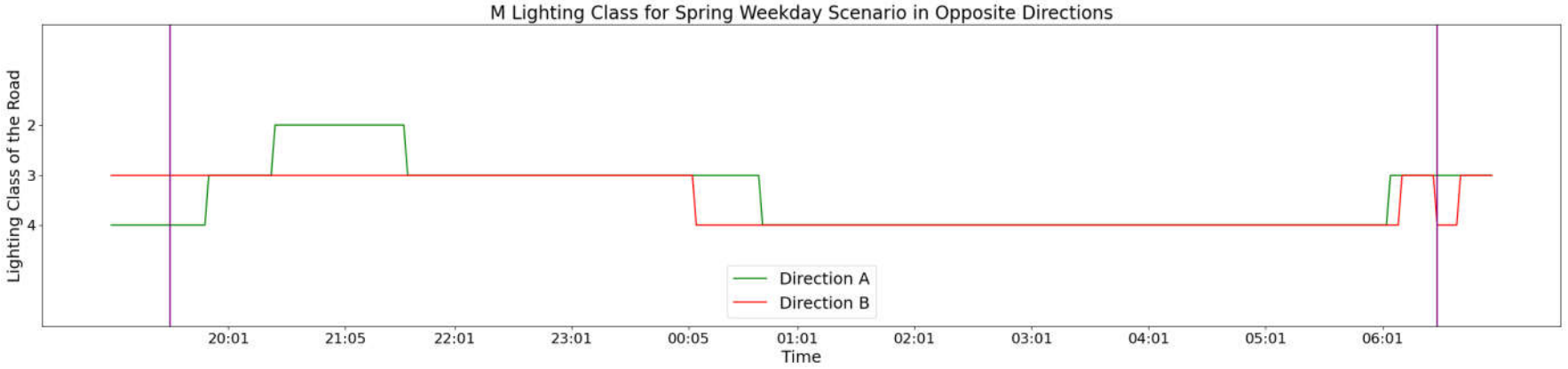

Figure A.10: M lighting class for spring weekday scenario in opposite directions.

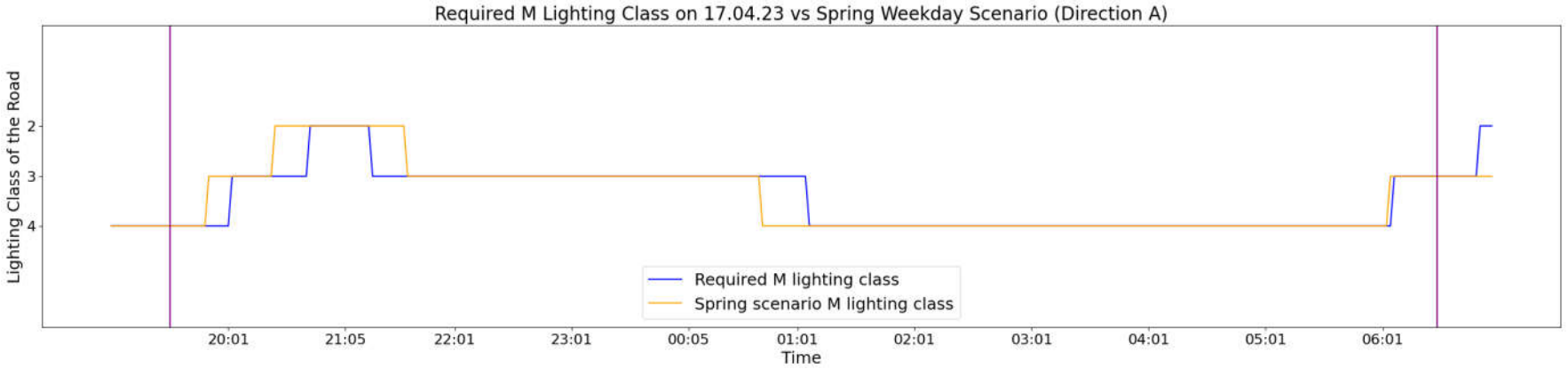

Figure A.11: Required M lighting class on 17.04.2023 compared to spring weekday scenario (direction A).

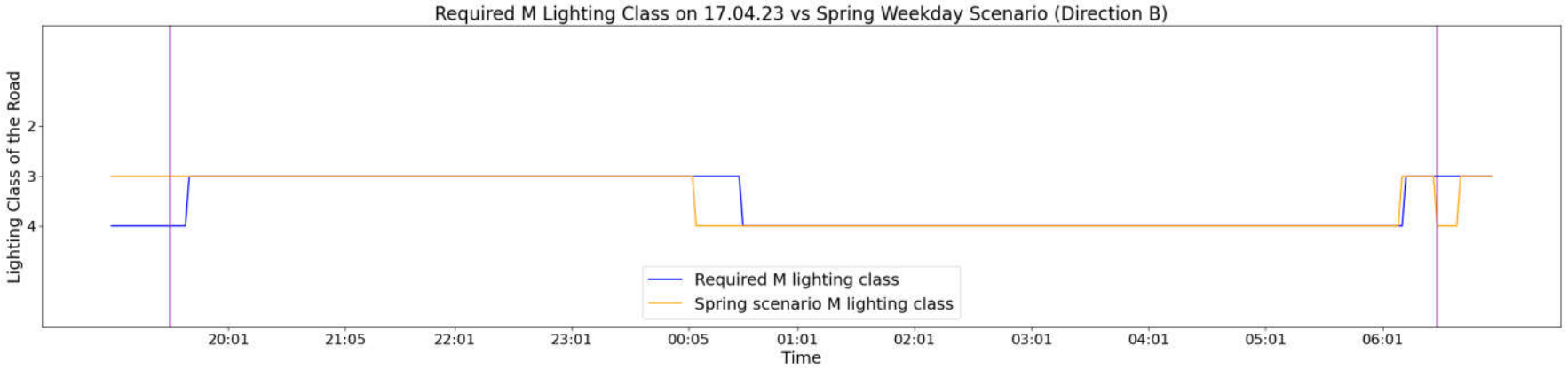

Figure A.12: Required M lighting class on 17.04.2023 compared to spring weekday scenario (direction B).

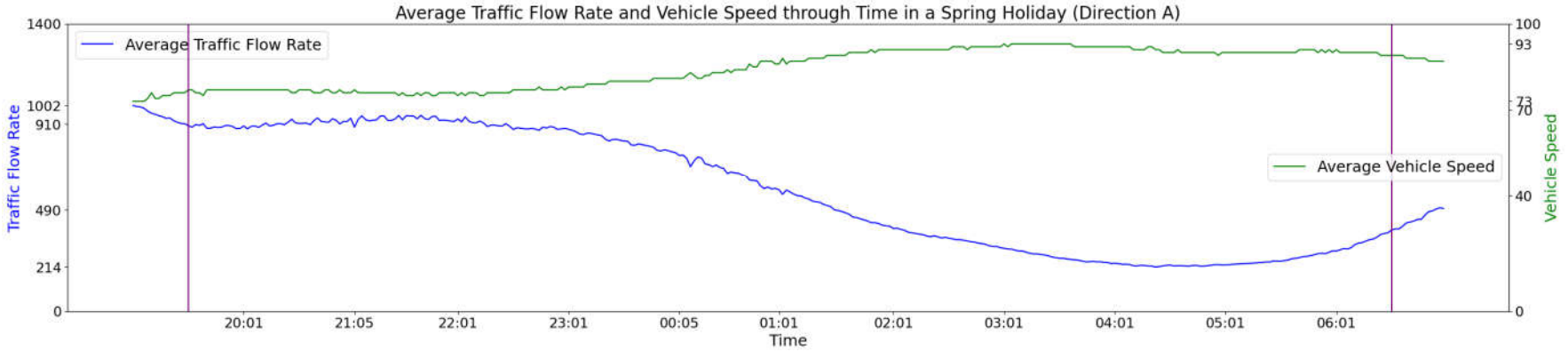

Figure A.13: Average traffic flow rate and vehicle speed through time in a spring holiday (direction A).

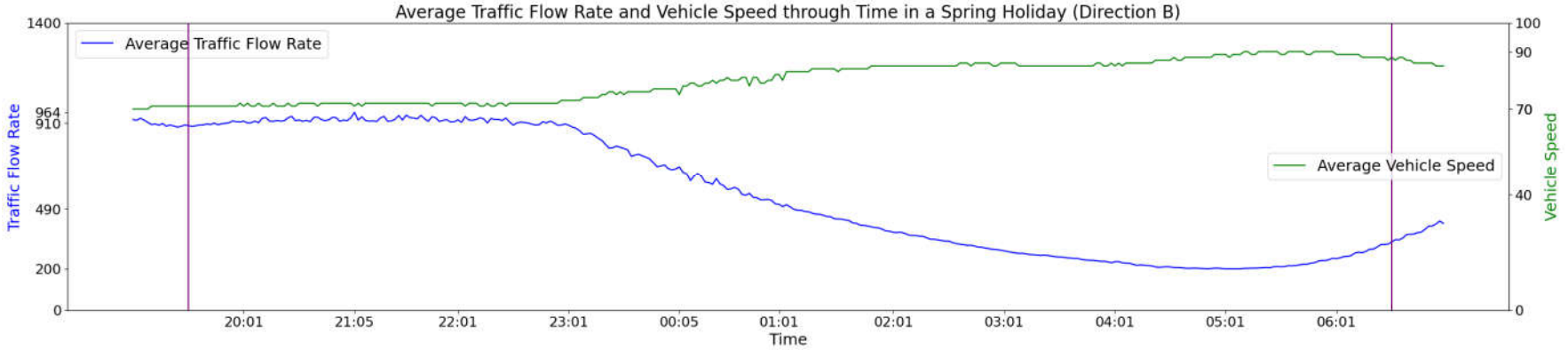

Figure A.14: Average traffic flow rate and vehicle speed through time in a spring holiday (direction B).

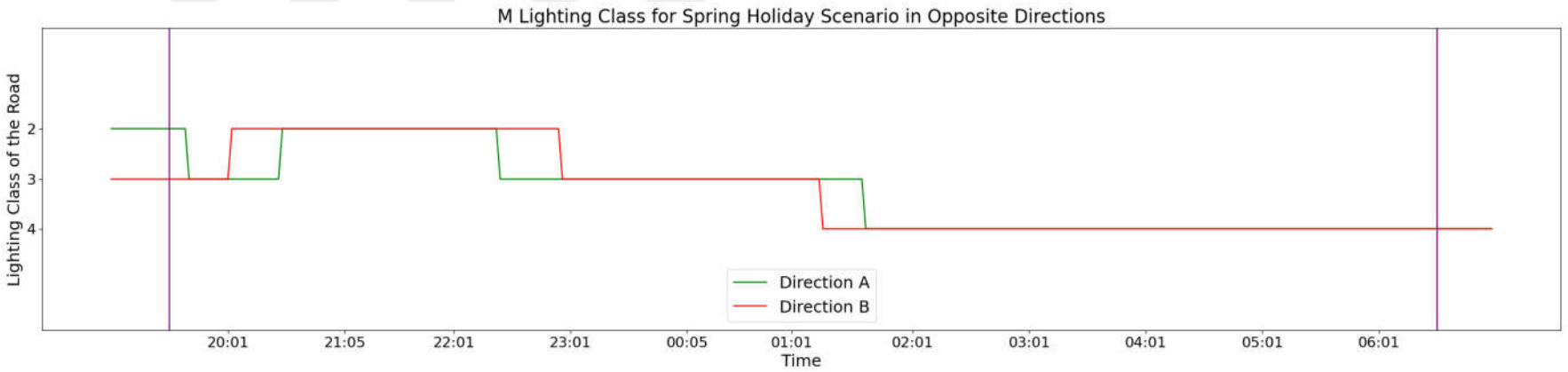

Figure A.15: M lighting class for spring holiday scenario in opposite directions.

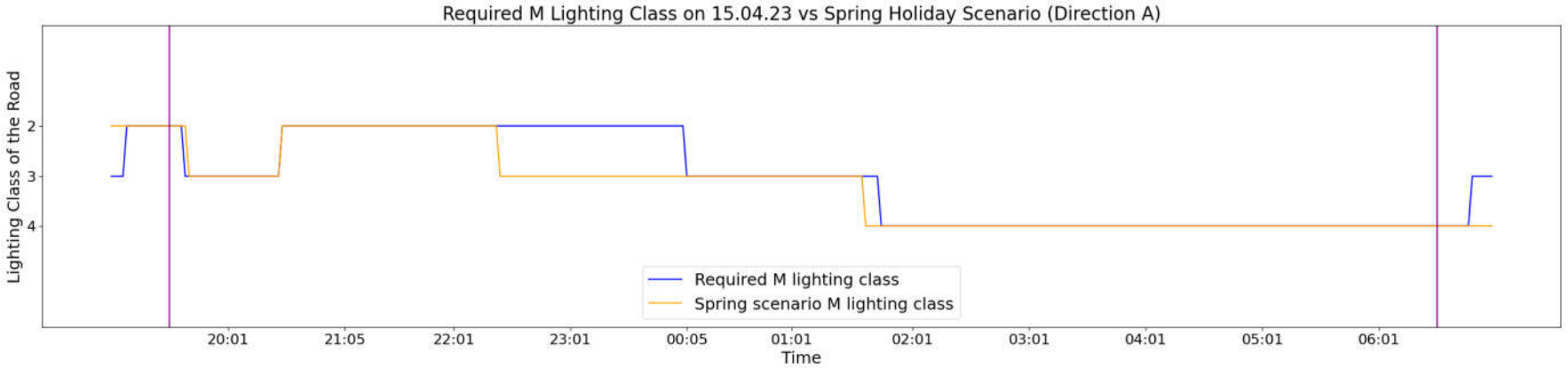

Figure A.16: Required M lighting class on 15.04.2023 compared to spring holiday scenario (direction A).

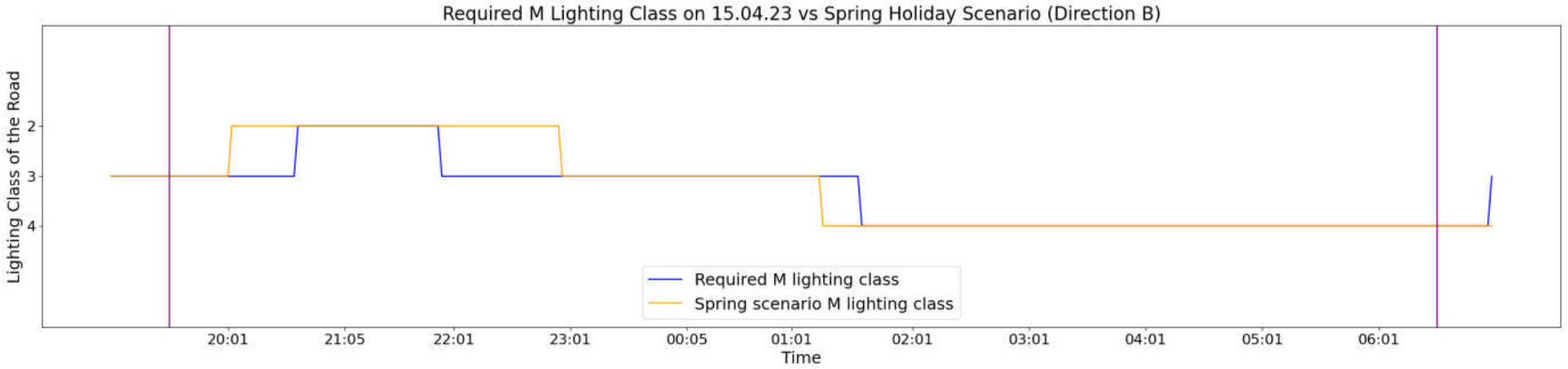

Figure A.17: Required M lighting class on 15.04.2023 compared to spring holiday scenario (direction B).

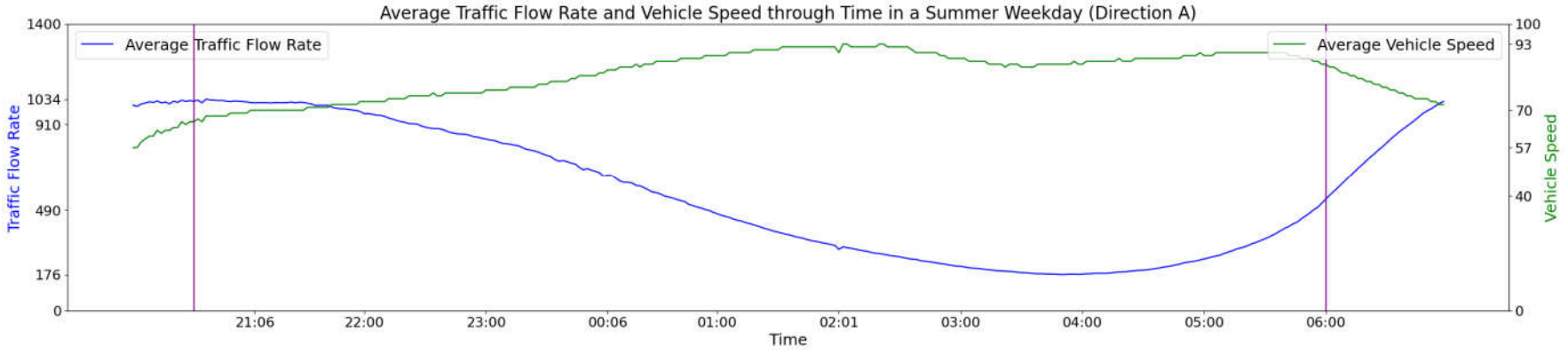

Figure A.18: Average traffic flow rate and vehicle speed through time in a summer weekday (direction A).

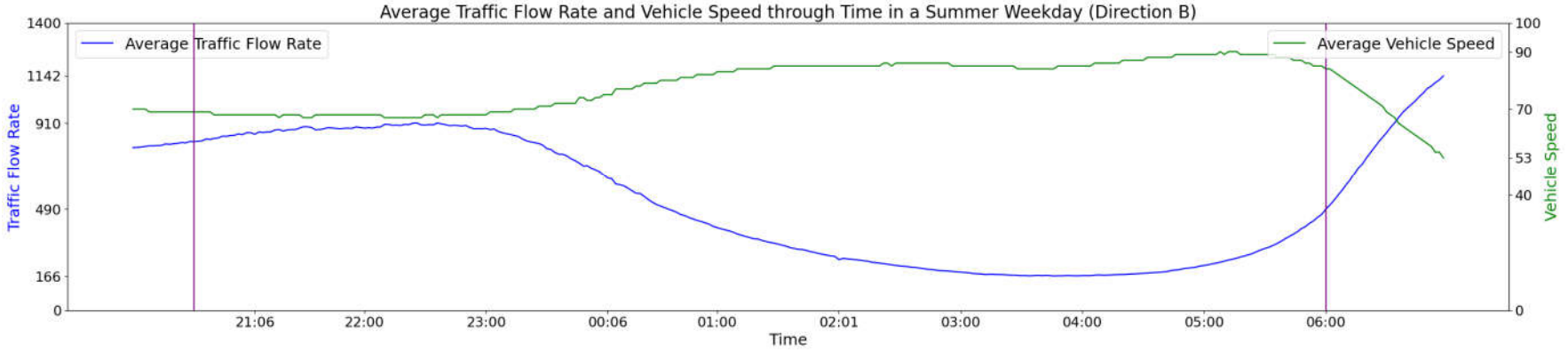

Figure A.19: Average traffic flow rate and vehicle speed through time in a summer weekday (direction B).

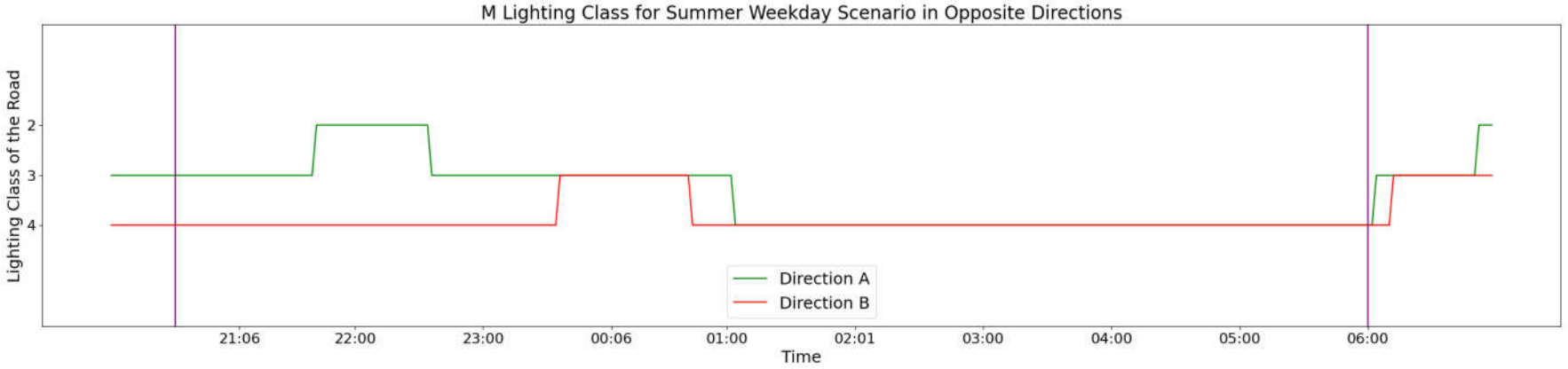

Figure A.20: M lighting class for summer weekday scenario in opposite directions.

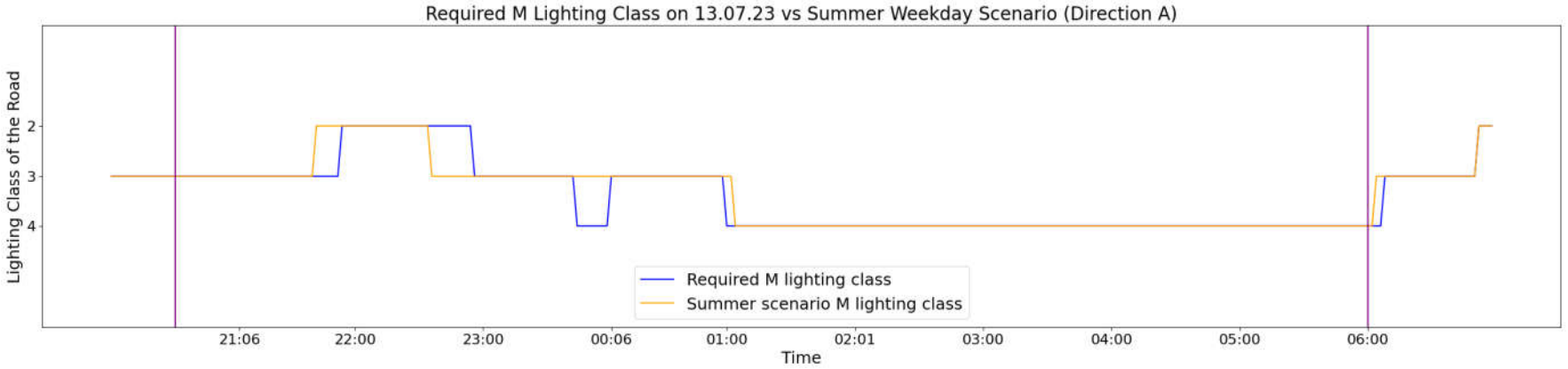

Figure A.21: Required M lighting class on 13.07.2023 compared to summer weekday scenario (direction A).

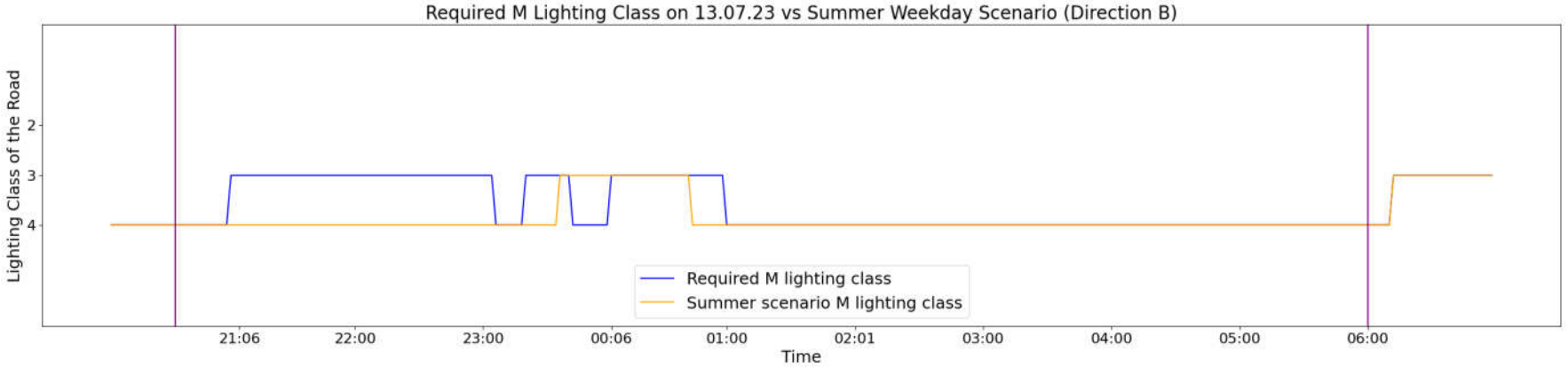

Figure A.22: Required M lighting class on 13.07.2023 compared to summer weekday scenario (direction B).

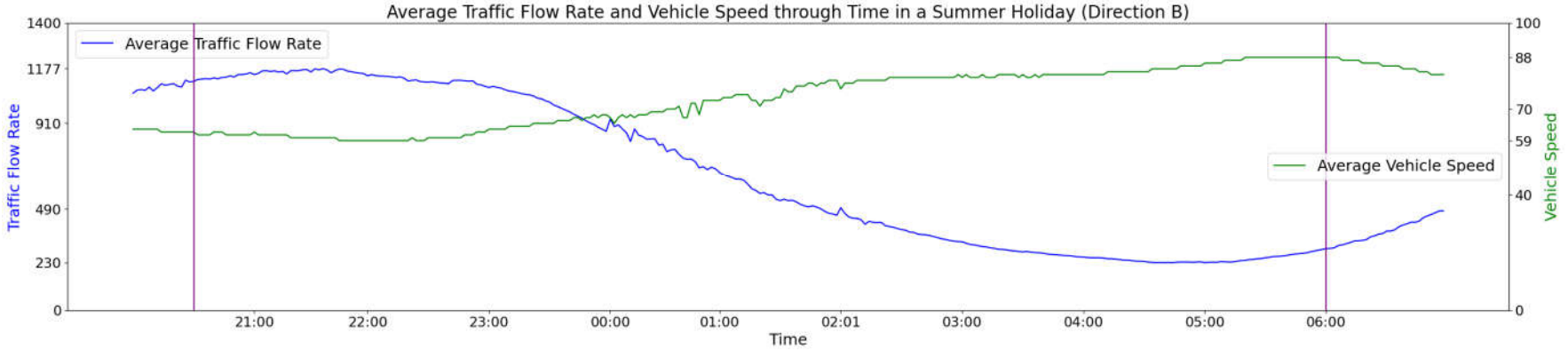

Figure A.23: Average traffic flow rate and vehicle speed through time in a summer holiday (direction B).

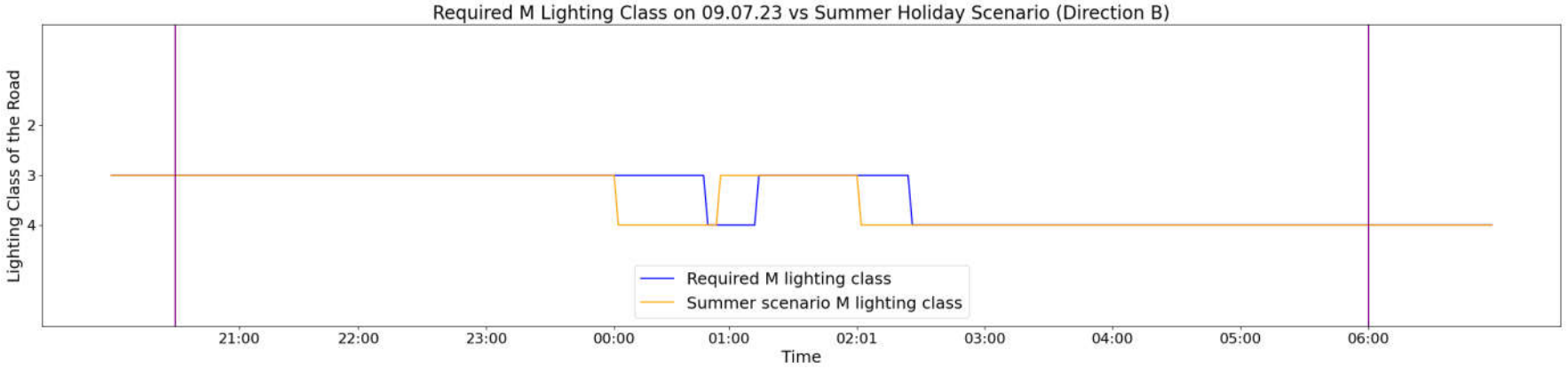

Figure A.24: Required M lighting class on 09.07.2023 compared to summer holiday scenario (direction B).

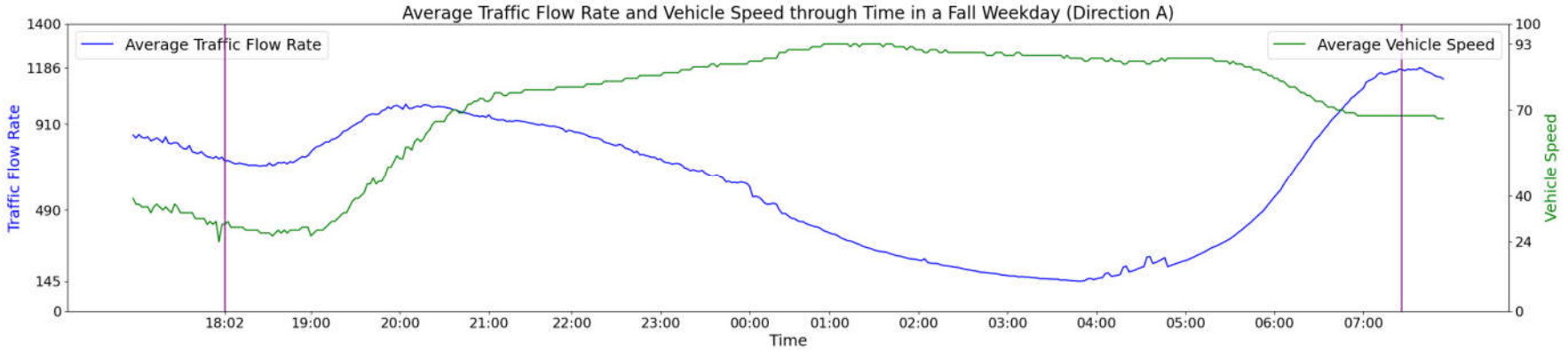

Figure A.25: Average traffic flow rate and vehicle speed through time in a fall weekday (direction A).

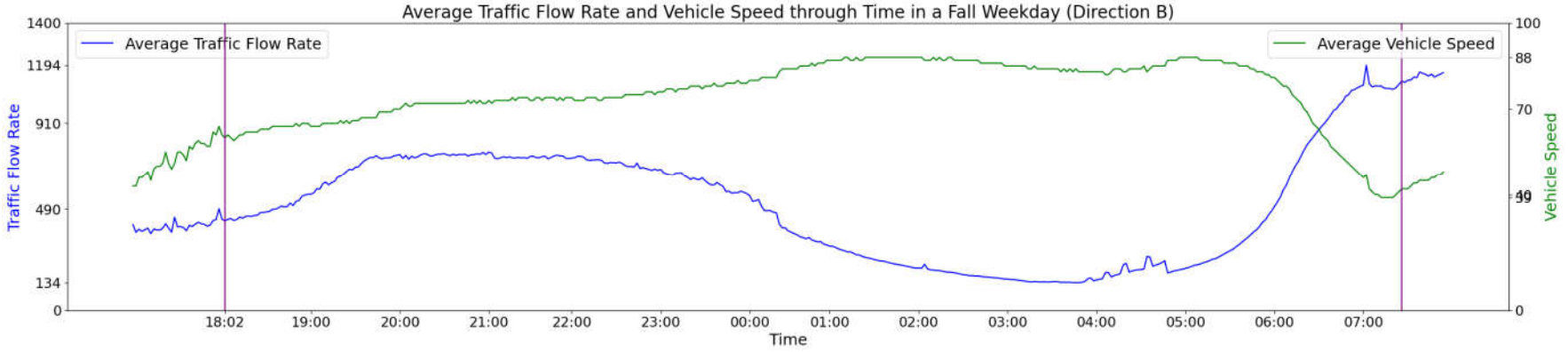

Figure A.26: Average traffic flow rate and vehicle speed through time in a fall weekday (direction B).

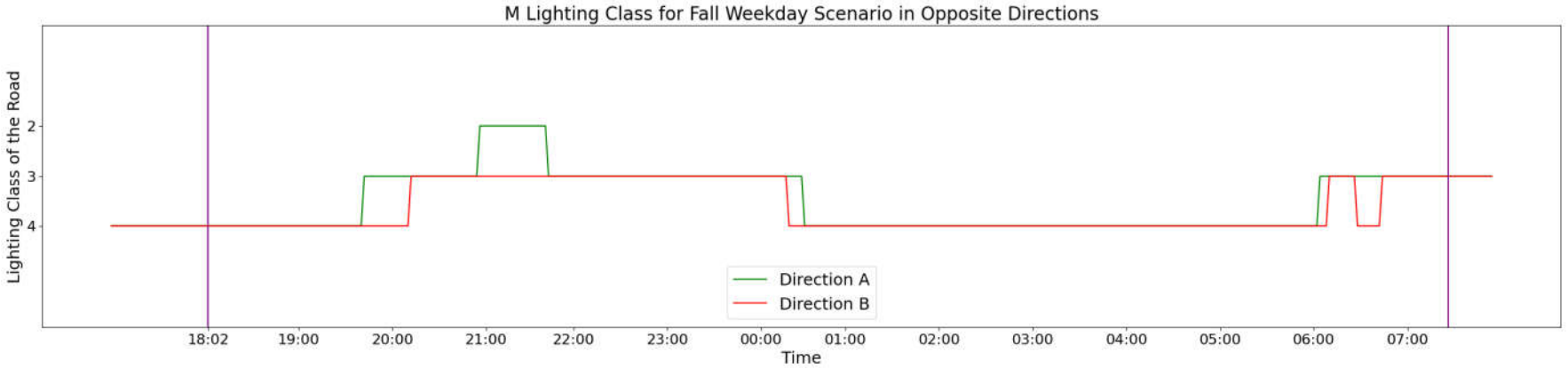

Figure A.27: M lighting class for fall weekday scenario in opposite directions.

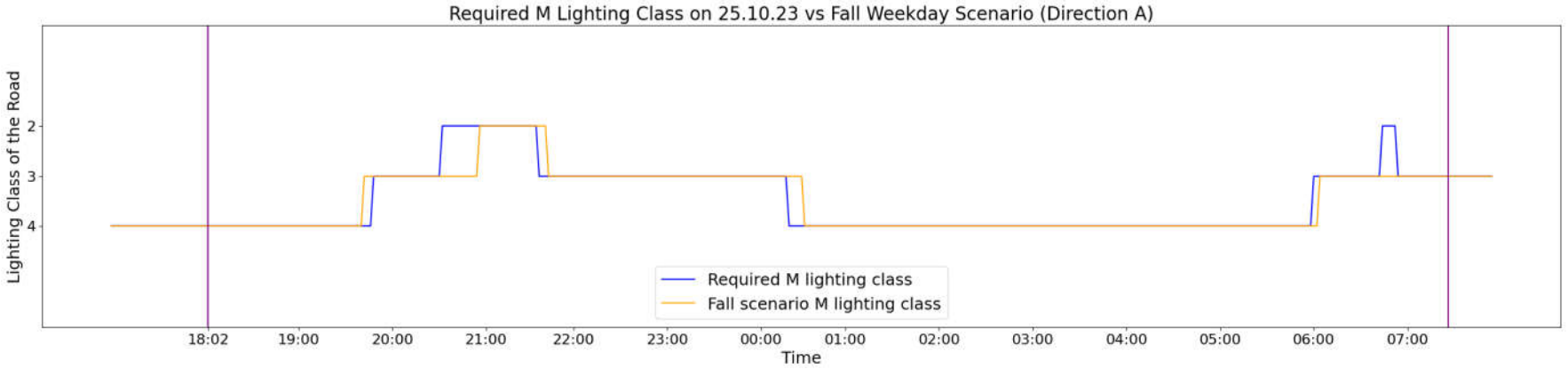

Figure A.28: Required M lighting class on 25.10.2023 compared to fall weekday scenario (direction A).

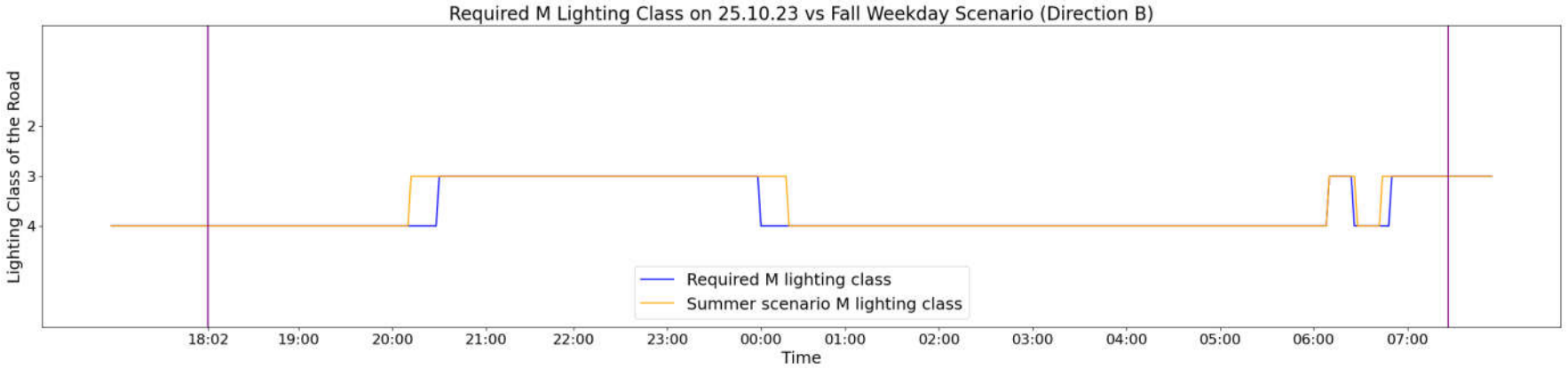

Figure A.29: Required M lighting class on 25.10.2023 compared to fall weekday scenario (direction B).

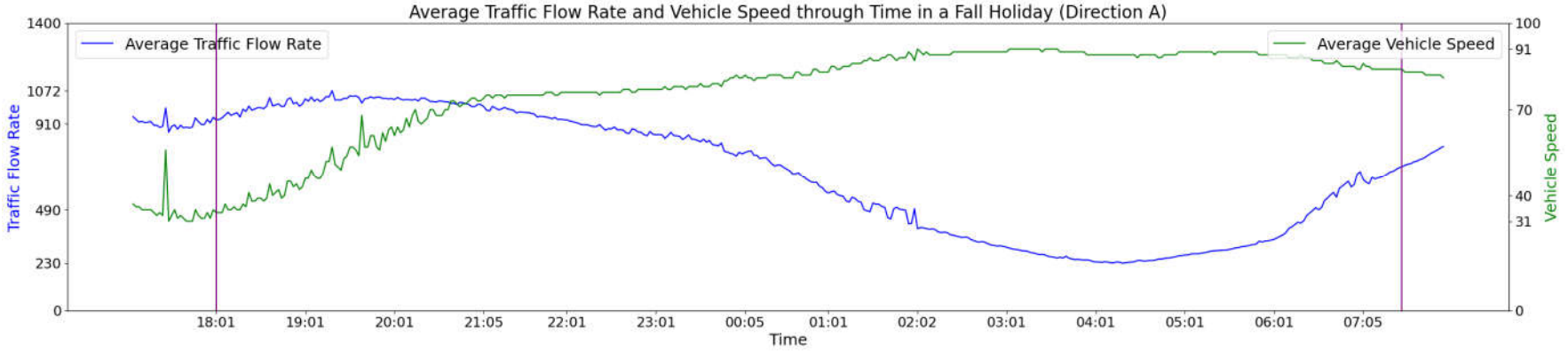

Figure A.30: Average traffic flow rate and vehicle speed through time in a fall holiday (direction A).

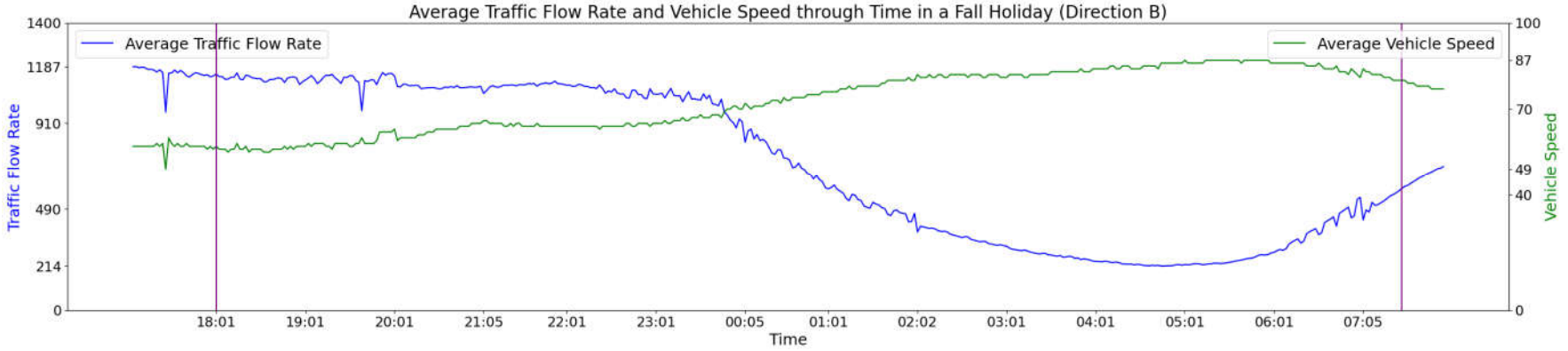

Figure A.31: Average traffic flow rate and vehicle speed through time in a fall holiday (direction B).

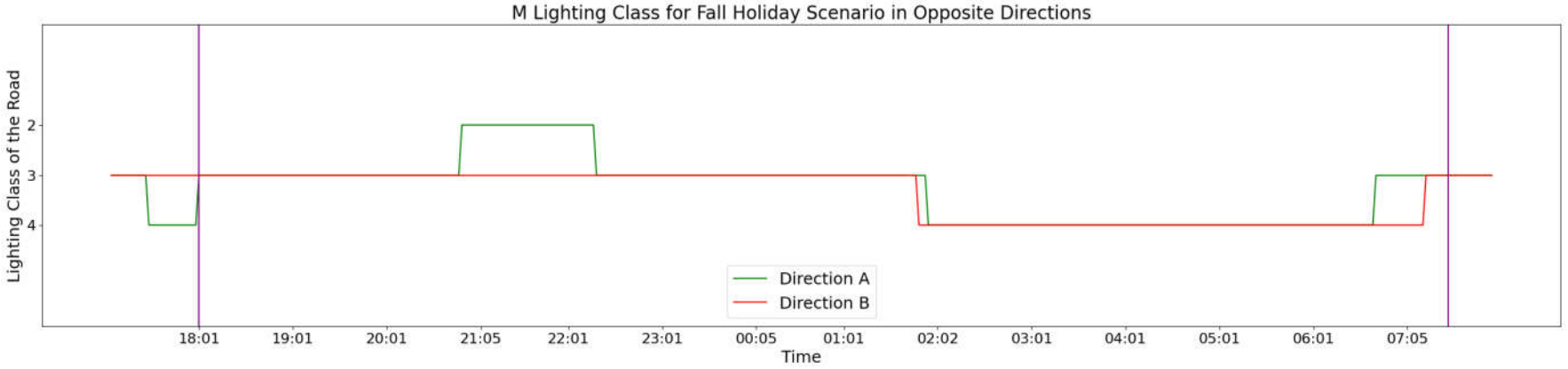

Figure A.32: M lighting class for fall holiday scenario in opposite directions.

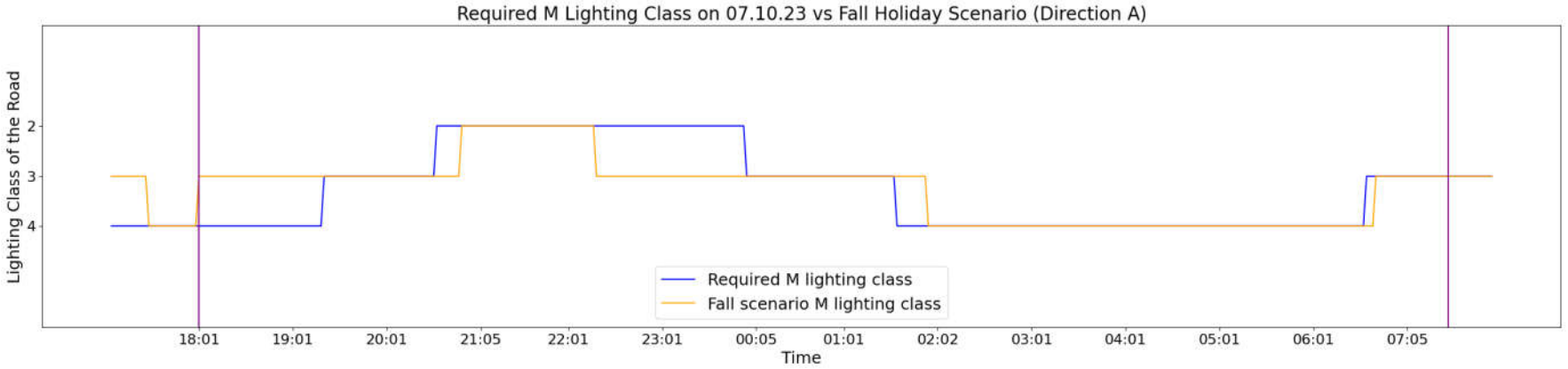

Figure A.33: Required M lighting class on 07.10.2023 compared to fall holiday scenario (direction A).

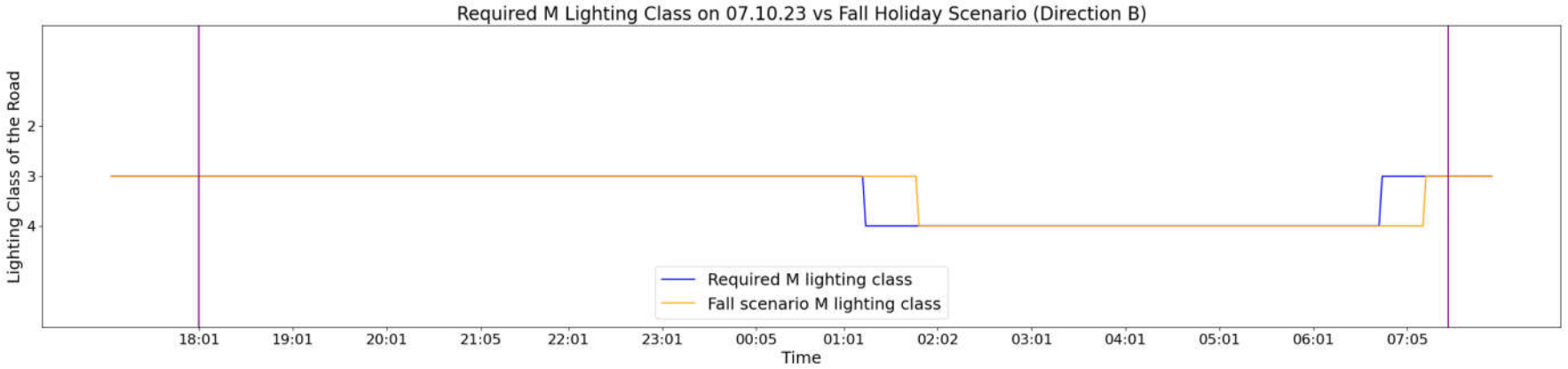

Figure A.34: Required M lighting class on 07.10.2023 compared to fall holiday scenario (direction B).

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