Faculty of Computer Science and Information Technology

Prediction based Lighting Control Scheme for Wireless Managed Streetlight Networks

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Prediction based Lighting Control Scheme for Wireless Managed Streetlight Networks

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgement has been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Thank you.

ABSTRACT

With the advent of a smart city that is embedded with smart technology, namely smart streetlight, in urban development, the quality of living for citizens has been vastly improved. Traffic-Aware Street lighting Scheme Management Network (TALiSMaN) is one of the apt smart streetlight schemes to date; however, it possesses certain limitations that led to network congestion and packet dropped during peak road traffic periods. Traffic prediction is vital in network management, especially for real-time decision-making and latency-sensitive application. With that in mind, this work analyses three low-complexity real-time prediction techniques, namely simple moving average, exponential moving average, and weighted moving average, to be embedded onto TALiSMaN, which aims to ease the network congestion. Additionally, this work proposes traffic categorisation and packet propagation control mechanism that uses historical road traffic data to manage the network from overload. The performance of these prediction techniques with TALiSMaN was simulated and compared with the original TALiSMaN scheme. Overall, the simple moving average showed promising results in reducing the packet dropped by 12.9% – 37.4% while capable of improving up to 2.9% of the streetlight usefulness experienced by the road users, when compared to the original TALiSMaN scheme, especially during rush hour.

Keywords: Traffic prediction, adaptive street lighting, smart cities, energy efficient, network congestion

Skim Kawalan Kesesakan untuk Mengurus Sistem Rangkaian Lampu Jalan

ABSTRAK

Melalui kemunculan bandar pintar yang tertanam dengan teknologi pintar, iaitu lampu jalan pintar, dalam pembangunan bandar, kualiti hidup untuk rakyat telah jauh lebih baik. TALiSMaN adalah salah satu skim lampu jalan pintar yang menjanjikan sehingga kini, ia mempunyai batasan tertentu yang menyebabkan kesesakan rangkaian dan paket menurun semasa tempoh lalu lintas puncak. Ramalan lalu lintas sangat penting dalam pengurusan rangkaian, terutama untuk membuat keputusan masa nyata dan sensitif kependaman. Dengan ini, tesis ini menganalisis tiga model ramalan lalu lintas jangka masa nyata, khususnya purata bergerak sederhana, rata-rata bergerak eksponen dan purata bergerak wajaran untuk diintegrasikan ke TALiSMaN, yang bertujuan untuk meredakan kesesakan rangkaian. Di samping itu, kertas mencadangkan pengkategorian lalu lintas dan mekanisme kawalan penyebaran paket yang menggunakan data lalu lintas sejarah untuk menguruskan rangkaian daripada beban. Dalam tesis ini, kita menilai prestasi model-model ini dengan TALiSMaN dalam persekitaran simulasi dan membandingkannya dengan TALiSMaN tanpa model ramalan trafik. Keseluruhannya, purata bergerak sederhana menunjukkan keputusan yang menjanjikan dalam mengurangkan paket yang disingkirkan sebanyak 12.9% – 37.4% sementara mampu meningkatkan sehingga 2.9% kegunaan lampu jalan apabila dibandingkan dengan skema TALiSMaN, terutama semasa jam sibuk.

***Kata kunci**: Ramalan lalu lintas, lampu jalan penyesuaian, bandar pintar, tenaga yang cekap, kesesakan rangkaian*

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LIST OF ABBREVIATIONS

AECR	Adaptive Energy Aware Cluster-based Routing
AI	Artificial Intelligence
ARIMA	Auto Regressive Integrated Moving Average
ASLS	Adaptive Smart Streetlight System
BPA-CRP	Balanced Power-Aware Clustering and Routing Protocol
CA-GPCR	Congestion-Aware GPCR routing
CH	Cluster Head
CoLBA	Collaborative Load Balancing Algorithm
DCT	Degree Constrained Tree
EBZ	Energy Balanced Zone-based
ECCM	Enhanced Congestion Control Mechanism
EDAL	Energy-efficient, Delay-aware Lifetime-balancing
EDR	Efficient Data Routing
EEDCF	Energy Efficient Distributed Clustering Algorithm based on Fuzzy
EMA	Exponential Moving Average
IR-DRA	In-Route Data Rate Adaptation
ISLC	Intelligent Streetlight Control
ISPLC	Intelligent System for Public Lighting Control
LSTM	Long Short-Term Memory
MCP	Minimum Conflicting Probability
MobileCC	Mobile Congestion Control
OHCR	On-Hole Children Reconnection
OLSR	in Optimised Link State Routing

PA	Prediction Accuracy
P-SEP	Prolong Stable Election Protocol
PDR	Packet Dropped Ratios
QHCR	QoS-aware and Heterogeneously Clustered Routing
QU-RPL	Queue Utilization based RPL
REE-VBF	Reliable and Energy Efficient Vector-Based Forwarding Protocol
RMSE	Root Mean Square Error
SHLMS	Smart Highway Lighting Management System
SMA	Simple Moving Average
SPT	Shortest Path Tree
SIF	Swarm Intelligence based Fuzzy
TALiSMaN	Traffic-Aware Street lighting Scheme Management Network
TEC	Total Energy Consumption
TU	Total Utility
WMA	Weighted Moving Average
WSN	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter begins with a brief history of conventional streetlight becoming an energy-efficient smart streetlight, following with the underlying problems and challenges on achieving a reliable network performance with high energy efficiency. The objectives, scopes, significance of the study and the methodology of this study is further elaborated.

1.2 Background of Study

Street lighting is an essential public service that ensures road safety for the public during the night (Velaga & Kumar, 2012). The number of streetlights increased when an area is getting urbanised. Thus, the energy consumption of street lighting also increased linearly with the increment of streetlights. According to Mohamed (2013), this has various impacts such that it has significantly affected the cities' energy use and burden the municipal budgets. With the notion of Networked Street lighting, also known as an intelligent street lighting system, street lighting can be operated autonomously by observing changes in the surroundings. Marino et al. (2017) indicated that the intelligent street lighting system can reduce high energy requirement of traditional streetlights while ensuring public safety and economic growth.

One of the ways to manage Networked Street lighting is implementing the Wireless Sensor Networks (WSNs) onto the streetlights. Application of WSN allows constant monitoring and autonomous operation. There have been a few attempts of adopting WSN on street lighting management, among them, distributed Traffic-Aware Street lighting Scheme

Management Network (TALiSMaN) (Lau et al., 2013) is one of the apt schemes for the adaptive street lighting system. Due to its distributed nature, TALiSMaN can perform dynamically and remotely with no human intervention. Based on Lau et al. (2013), TALiSMaN was equipped with WSNs to improve the efficiency in power consumption and to facilitate network communication among the streetlights effectively.

The urbanisation process and the expansion of urban population had brought great pressure to the urban traffic management that results in road traffic congestion (Diao et al., 2018). However, due to the operation nature of TALiSMaN, increasing traffic on the road is a disadvantage as it causes delay on relaying real-time data among streetlights. The scheme adopted multi-hop WSN technology and utilised refined flooding routing protocol to broadcast sensor-generated data among streetlights. Although flooding routing protocol is simple and efficient in broadcasting packets to adjacent nodes (Mangrulkar & Atique, 2011), TALiSMaN experiences notable packet drops with increasing road traffic. Due to TALiSMaN operation nature, constant generating and broadcasting sensory data of passing-by road traffic to coordinate lighting operations of adjacent streetlights. The coordination in the increasing road traffic, causes flooding of sensory data within its WSN.

In the smart street lighting scheme, even a slight delay is unbearable as the operation of networked street lighting is dependent on the prompt information exchange between streetlights. Street lighting expects instant lights on before the commuters are approaching. A slight delay of the scheme could lead to street lighting unable to illuminate on time, thus reducing commuters' visibility and sense of safety when in a dark environment. This is vital as it defeats the purpose of having street lighting.

Road traffic forecasting is crucial for efficient road networks management (Singh et al., 2019). In this study, we adopted road traffic forecasting to ease the severity of packet drop and network congestion in TALiSMaN during heavy road traffic scenario, thus maintaining the better of its operation. This study aims to use the road traffic volume predictor to mitigate the possibility of sensory data flooding in TALiSMaN. This is to ensure the attainability of street lighting throughout the entire night, thereby achieving street lighting usefulness from evening until the next morning. We evaluate the performance of the proposed solution with three moving average technique and compare with the original TALiSMaN scheme in linear and cross junction network topologies. From the simulation results, the proposed solution reduces packet dropped and improves the usefulness of TALiSMaN scheme during heavy road traffic scenarios.

1.3 Problem Statement

Although TALiSMaN performs well in non-congested road traffic scenario, Lau (2016) discovered that it suffers from network congestion and packet drops at the rate of 23% to 29%. Due to the packet dropped rate, TALiSMaN is unable to deliver a higher percentage of streetlight usefulness, making TALiSMaN scheme unreliable and inefficient to operate. Since the performance of the applied routing protocol is not the main focus of the existing research, TALiSMaN adopted a refined flooding protocol due to its simplicity to broadcast the information to designated streetlights, ensuring that the streetlights are turned on and off before the passing-by road traffic arrives and departs. The flooding of the network packet occurred within 100 m radius of the source streetlight that detects the passing-by road traffic. Owing to that, packet transmission period is limited to less than 2 seconds to ensure streetlights within 100 m radius were always turn on before arrival of passing-by road traffic. The adopted routing protocol, however, has several limitations.

Firstly, packet drops occurred during the broadcast process. Once motorist is detected, the sensors require to continuously sense for motorists, broadcast, and relay data to the streetlights within 100 m radius. Therefore, multiple sensors will broadcast simultaneously, increasing the probability of packet collision during heavy road traffic period. This scenario could lead to packet drops. This issue could have a severe effect to the scheme as it could cause the streetlights to remain on all night, requiring more energy to operate the streetlights, resulting in energy inefficiency.

Secondly, network congestion occurred as TALiSMaN was designed to generate and broadcast sensory data at the rate of 2 Hz. The continuous broadcast of the data packet ensured that the information relayed was received by neighbouring streetlights. When the network is congested at heavy road traffic period, the neighbouring streetlights may not receive the information and remain switched off. Thus, unforeseen circumstances may occur if motorists do not have enough brightness to observe obstacles that lay upfront. Besides, energy used to transmit and receive the packets may be wasted and caused drainage of useful energy.

Thirdly, the occurrence of packet drops is notably higher in certain streetlight topologies. The network topology represents the distribution structure of the streetlights on the selected road section. For example, the T-junction road topology has more streetlights positioned at the intersection to ensure visibility at night. When the streetlights are arranged close together, the density of nodes increase. Fu et al. (2020) stated that the increment in sensor nodes leads to an increment of the packets being broadcast to adjacent nodes. Sunitha et al. (2017) explained that the occurrence of packet drops in a real-time application may

shorten network lifetime and result in performance degradation while causing the street lighting unable to function as required.

Therefore, if the issue of network congestion and packet loss is not overcome, TALiSMaN may not operate at its optimum performance.

1.4 Purpose of the Study

This study aims to reduce the packet drop while maintaining or improving the usefulness of TALiSMaN in heavy road traffic scenarios. The objectives of this study are outlined as follows:

i. To analyse the packet dropped rate and the effect in TALiSMaN.

ii. To propose a predictive control scheme that can improve the performance of TALiSMaN by reducing the packet drop while maintaining or improving the performance of the street lighting during heavy road traffic scenario.

iii. To evaluate the performance of proposed solution in terms of packet drop, energy usage and utility of the proposed scheme against TALiSMaN.

1.5 Scope of the Study

The scope of this study is as the following:

i. The study will be conducted via simulation.

ii. Three different real-time, short-term road traffic prediction techniques i.e., SMA, EMA, and WMA are considered to study the performance of the existing network protocols and the newly proposed in this study.

iii. Different prediction windows, i.e., 5 minutes, 10 minutes, 20 minutes, and 30 minutes are considered for real-time road traffic prediction.

iv. Two different network topologies i.e., linear and t-junction topologies are considered in this simulation. These topologies are observed using aerial imagery.

1.6 Significance of the Study

The importance of this study is to reduce the packet drop while maintaining or improving the usefulness of the streetlight during heavy road traffic scenarios. Thus, TALiSMaN can perform efficiently while enhancing the visibility, social inclusion, and sense of safety for road traffic throughout the night while reducing crime rates and financial burden of the country.

1.7 Chapter Overview

This thesis consists of five chapters. Chapter 2 describes the detailed background on networked street lighting, limitation of selected networked street lighting scheme, routing protocol adoption in networked street lighting and traffic prediction techniques. In Chapter 3, TALiSMaN with predictive control scheme is proposed to address the limitation of TALiSMaN during rush hour. Chapter 3 includes a detailed explanation of the design and development of the proposed scheme based on the considered prediction techniques. Chapter 4 presents the implementation and performance analysis of TALiSMaN with predictive control scheme against TALiSMaN scheme to determine the reduction of packet dropped ratios (PDR) while maintain or improve the usefulness of streetlight experienced by road traffic during traffic peak period. Chapter 5 concludes the thesis by summarising the contribution and illustrating the future work of this research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter discusses an overview of the networked street lighting, followed by the advancement and summary of networked street lighting. Then, the potential routing protocols capable of supporting TALiSMaN are categorised and reviewed in this section. Next, the prediction models as the alternative solution to support TALiSMaN is analysed and reviewed.

2.2 Networked Street lighting

The notion of smart cities is still emerging to alleviate the challenges faced due to rapid urban population growth. Smart Cities refers to the application of technologies to produce intelligent, integrated, and efficient public services in various fields to enhance the quality living (Washburn et al., 2009). A few of the formidable challenges created by the growth of population density include high energy consumption, traffic congestion, insufficient resources, and pollution. Various cities throughout the world show devotion in the development projects involving the fields of energy efficiency (Beccali et al., 2015, Al Irsyad & Nepal, 2016), which include street lighting, energy storage in batteries, etc.

Street lighting energy usage is gradually occupying a notable portion of cities' energy consumption, especially in densely populated cities. Mustafa et al. (2017) specified that most of the current street lighting systems are still adopting traditional continuous illumination lighting with a full night-lights scheme. This lighting system is consuming excessive energy

and exhausting the lamp lifecycle when vehicles are not continuously occupying the road throughout the operation hour.

For that reason, numerous studies on smart street lighting have been proposed. One of the techniques is adjusting streetlights according to real-time road occupancy. For instance, when there is no vehicle on the road, the lamp can turn off and vice versa, to optimize the energy usage while achieving the lighting requirements. Some researchers even introduced more advance method to control the lighting system such as fuzzy system (Yang et al., 2011), image processing (Carrillo et al., 2013), cooperative methods with WSN (Zhang et al., 2013), formal methods (Wojnicki, 2014), AI (García et al., 2014), and predictive control (Barra & Rahem, 2014).

Mukta et al. (2020) expressed that although various lighting approaches proposed a prototype that showed an immense potential to mitigate energy wastage issue in the traditional lighting system, their competency and longevity for practicality are scarcely noticed and studied in literature. Hence, several prospective lighting schemes are described and reviewed in subsections below for further experimentation to ensure seamless operation.

2.2.1 TALiSMaN and TALiSMaN-Green

The schemes consist of two variants, namely TALiSMaN and TALiSMaN-Green, where the on-grid system was adopted by TALiSMaN and the off-grid system was adopted by TALiSMaN-Green. TALiSMaN is a traffic-aware lighting scheme management network that uses sensors from a distributed network to autonomously monitor the brightness of each streetlight (Lau et al., 2013). TALiSMaN is designed to adapt to the different behaviours of road traffic instead of relying on central operational control, allowing each streetlight to operate independently using a short-range mesh network.

The scheme uses sensors to detect pedestrians and motorists, then changes the streetlight's lighting condition to suit different road users' needs while optimizing the use of energy. The optimum lighting condition for a pedestrian to receive the utmost utility of the streetlight is within the range of 150 m in all directions (Lau et al., 2014). To show the usefulness of street lighting, TALiSMaN adopted a streetlight usefulness model to assess the utility and practicality of street lighting in aiding the range of vision and provide sense of security for pedestrian, to travel during the night. Based on Lau et al. (2014), the streetlight usefulness model for a pedestrian is given by:

$$U_{ped(avoid)} = 10^{-1} \int_{0}^{10} \gamma(x,t)\, dx \qquad \text{Equation 2.1}$$

Where $\gamma(x,t)$ is the ratio of brightness level at x ahead of a pedestrian at time t to the required brightness level of the pedestrian travelled road.

For efficient energy usage, the light intensity of the streetlight decreases gradually in the range of 150 m from every direction (distance between S1 to S5 and S5 to S9) when the sensors detect the presence of pedestrian progress further while ensuring ample of visibility in that environment, as shown in Figure 2.1.

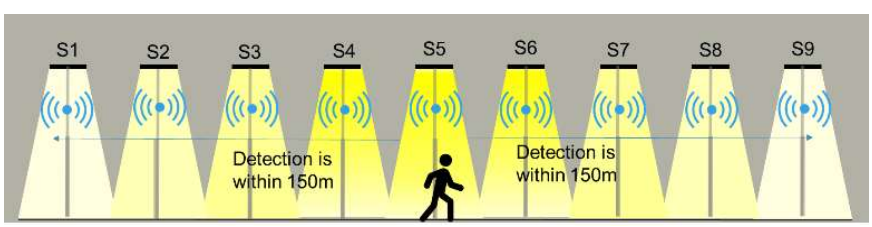


Figure 2.1: TALiSMaN for a pedestrian (Lau et al., 2014).

As for motorists, streetlights within a 100 m radius from the detected vehicle are completely turned on for motorists to experience the utmost usefulness of the streetlight, as

presented in Figure 2.2. The scheme adopted streetlight usefulness model to measure the usefulness and practicality of street lighting in broadening the range of vision for the motorists beyond that provided by vehicle headlights, to avoid collision while driving during the night. Based on Lau et al. (2014), the streetlight usefulness model for a motorist is given by:

$$U_{mot}(t) = 100^{-1} \int_{0}^{100} \gamma(x,t)\, dx \qquad \text{Equation 2.2}$$

Where $\gamma(x, t)$ is the ratio of brightness level at x ahead of a motorist at time t to the required brightness level for the road where the motorist is travelling on.

While providing various lightning distributions for different road users' needs, TALiSMaN also emphasises energy efficiency. Lau et al. (2014) claimed that TALiSMaN can lessen energy usage by 45% – 98% according to the road traffic condition.

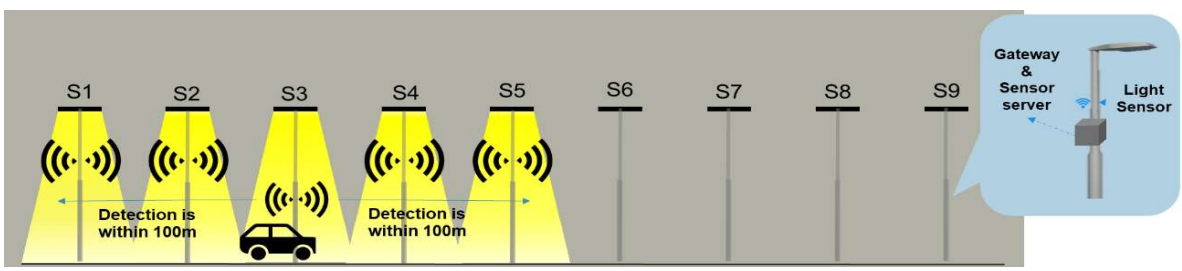


Figure 2.2: TALiSMaN for a motorist (Lau et al., 2014).

In TALiSMaN, consistent delivery of data and network congestion control are necessary to achieve the full potential of TALiSMaN. Since the sensor nodes in TALiSMaN scheme are unable to distinguish the travel direction of the road traffic, all the streetlights that detected the users will continuously broadcast the data to the adjacent streetlights within the predefined perimeter via a refined flooding protocol. In other words, if the road traffic is

located at S5 in Figure 2.1, the streetlight will start broadcasting data to S4 and S6. If S1 to S9 is within 150 m range, then the broadcast will proceed from S4 to S3, S6 to S7, and continues the broadcasting until S8 to S9 and S2 to S1. The broadcast of the data packet will repeat every 0.5 seconds. When the road traffic approaching to S6, S5 will still broadcast the same data to other streetlight, and at the same time, S6 has also started to broadcast the same data similar to S5, to inform other streetlights the distance of road traffic and to set the light intensity based on user's distance.

As mentioned above, TALiSMaN-Green is an enhanced version of TALiSMaN that adopted every functionality of TALiSMaN while employed a solar panel and battery to power the streetlight. The scheme can predict the next sunrise and the energy demand to operate throughout the night (Lau et al., 2014). Additionally, the scheme can preserve energy by controlling the brightness of the streetlight based on the information predicted. TALiSMaN-Green showed abundant capabilities and is beneficial for remote areas, but its operation is restricted by the maximal energy available as the batteries have limited capacity for energy storage. The off-grid streetlights may not function when there is no direct sunlight, wind, or when all stored energy is completely used up. Since the batteries are big and heavy to carry around, especially to rural or distant areas, it is not feasible to change the batteries once it fails to operate. Although TALiSMaN-Green can calculate the exact usable amount of energy while controlling the energy used throughout the night, but the occurrence of network congestion during packet transmission is undeniable, which may cause the misbehaviours of the scheme.

2.2.2 Intelligent System for Public Lighting Control

Intelligent System for Public Lighting Control (ISPLC) intends to introduce a centralise street lighting control and intelligent management in the smart cities to minimise lighting cost and unnecessary illumination (De Paz et al., 2016). ISPLC is integrated various AI approaches to predict illumination cost based on road traffic flow to adjust lighting levels while reduce energy usage based on different zone cluster. The system is designed in a modular architecture to easily adapt to the existing illumination system. The system consists of a web application for observation and management, streetlight hardware management, luminosity management, and energy consumption viewer. On the server stack, it contains data source, data analysis, and luminosity pattern generator. For communication, the system relies on a router to access the internet connection between the software stack and lightning pole. De Paz et al. (2016) revealed that the system is adaptable to present illumination systems while reducing cost and energy usage. Despite its advantages, the system may require additional costs in terms of the equipment, development, set up, and computation resource. The system requires human intervention in certain occasions.

2.2.3 Smart Highway Lighting Management System

Smart Highway Lighting Management System (SHLMS) is proposed to improve highway illumination based on road occupancy while reducing the illumination cost (Mustafa et al., 2017). The SHLMS employed WSN and divided the road into sections for vehicle detection purpose, where each section is the distance between the two consecutive streetlights. Each section is monitored by two streetlights that acted as the WSN nodes. In Figure 2.3, the streetlight of the section is initially turned off or dimmed when no vehicle is detected; else, the streetlight is turned on with full brightness. According to Mustafa et al.

(2017), the proposed control has a potential energy saving of 57.4% compared to traditional lightings.

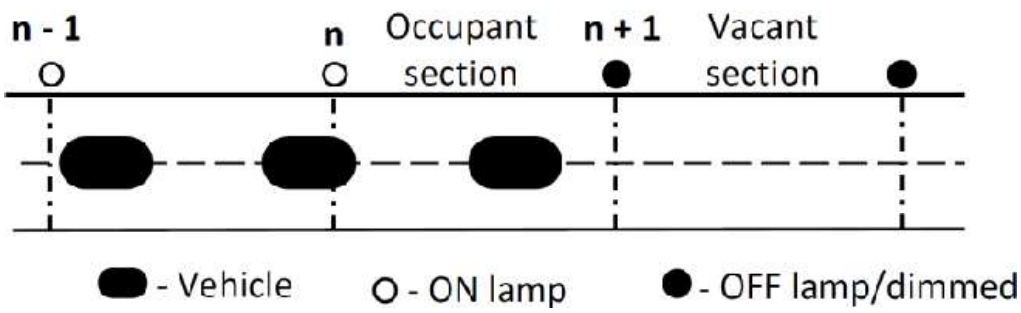


Figure 2.3: Sensor nodes arrangement across the road adopted from (Mustafa et al., 2017).

Although SHLMS shows potential capability in light traffic scenario, the on and off mechanism is not suitable for heavy road traffic scenario. As the road traffic volume increases, the streetlight may turn on and off instantaneously, thus causing visual disturbance to the road traffic. The reason is that the streetlight only turns on when the vehicle is arriving at the section and turn off or dim when it leaves the section. This might unintentionally cause traffic accidents as road traffic might not be able to perceive what lies ahead of them.

2.2.4 Intelligent Streetlight Control with RFID

Zeng et al. (2018) proposed an Intelligent Streetlight Control (ISLC) applied Radio Frequency Identification Technology (RFID) reader on each streetlight to detect vehicle and dynamically control the streetlight depending on the roads condition. The system will then calculate the vehicle speed and determine the total streetlight to turn on in advance. The system also implemented a fuzzy control algorithm to observe and evaluate the readings of the RFID sensor data for accurate adjustment of the streetlight intensity. The effectiveness of the system is verified via simulation and results showed that the system could control the street lighting based on the fuzzy decision and minimise energy consumption. However, the

use case of the system does not consider the pedestrian and does not favour the high road traffic volume scenario. Besides, this scheme requires each streetlight to attach with RFID reader and each vehicle to attach a vehicle tag information to detect and retrieve vehicle's information, which may lead to an increase in production cost.

2.2.5 Adaptive Smart Streetlight System Approach

Adaptive Smart streetlight System (ASLS) employs sensors onto the streetlights to adapt to different climatic conditions in day and night and presence of road traffic in the night while record the road traffic and environmental conditions to the cloud (Salman et al., 2019). ASLS aims to provide independent and progressively enhance the lighting framework while minimising energy consumption. The system turned on the entire streetlights when it detected fog or rain in either day time or night time, and when the infrared sensor detected the passing by vehicles during the night. The system will alarm the Road Maintenance Department if the light-dependent resistor sensor fails to function. The study only focuses on streetlights in front of a housing area with less road traffic condition. The author presented a proof of concept for the proposed solution and has not been thoroughly tested, especially in crowded road traffic condition, where unforeseen circumstances may arise.

2.2.6 IoT-Enabled Relay Network based System.

IeRN is an IoT enabled system that adopted the cooperative relay networking approach to control the lighting based on traffic situation (Rahman et al., 2020). The streetlights situated in front of the toll plaza acted as the anchor nodes and control centre, whereas the streetlights beside the toll are grouped into segments and acted as relay streetlights. The streetlights are attached with IoT box, where the toll streetlight detects the presence of motorists and propagate the information to the following relay streetlights within

a predefined segment to switch on the light before the vehicle arrives. The control centre is equipped with Global System for Mobile Communication (GSM) to alert the maintenance department via Short Message Service (SMS) if any attention is required. The proposed solution is designed to ensure the system is cost-effective, provides visual comfort to motorists, and the capability to reduce energy consumption. The performance of IeRN has been assessed to determine a suitable communication module between LoRA and IEEE 802.15.4 for IeRN. In this study, the authors claimed that 802.15.4 is more costly despite having less end-to-end delay than LoRA, hence LoRA is chosen as the communication module of the system. While the study indicated the expected cost of the system production, integration with existing streetlights may require additional cost. Rahman et al (2020) stated that the limitation of this work is the consideration of less crowded highway traffic condition using a low-cost communication module, LoRA where the performance of the system may deteriorate when applying in crowded traffic condition due to unanticipated network overhead.

2.2.7 Discussion

This section reviewed several state-of-the-art street lighting schemes that consist of similar characteristics where most of the scheme can achieve efficient energy consumption with the integration of WSNs to facilitate network communication and allow remote control of the streetlights. Besides, most of the reviewed schemes are sensitive to delay in data transmission as it requires to receive and respond to instantly turn on streetlight before the vehicle arrives. The communication channel adopted include flooding routing protocol, DALI protocol, NRF24L01 radio transceiver, RFID, ESP-NOW Protocol and LoRA.

The foremost factor to determine a suitable street lighting system for this study is a system that has a distributed architecture. A distributed lighting system allows the system to perform dynamically and remotely without human intervention, whereas a centralised lighting system requires a base station or designated central node to process all requests to operate the lighting poles in a designated area. Based on the reviewed schemes, TALiSMaN and SHLMS are distributed system while ISPLC, ISLC, ASLS and IeRN schemes are a centralised system. In comparison with centralised lightning scheme, a decentralised scheme like TALiSMaN is more efficient and reliable. When a node in TALiSMaN fails, it will insignificantly affect the whole system (i.e., only affecting the preceding and succeeding section). The decentralised approach also makes communication between nodes less complicated.

The next factor is the capability and reliability while operate using off-grid power supply. Most of the existing WSN based streetlight solutions become inadequate or restricted as their operational hour depending on weather conditions and limited energy storage (Guo et al., 2017). A reliable off-grid powered street lighting system is beneficial when grid power is inaccessible or during a power failure. Besides, the overhead for the off-grid power system is lower than the installation of grid power lines in remote areas. Lau et al. (2014) mentioned that TALiSMaN scheme could implement in a rural area without the support of electrical grid street lighting system or in an urban area by implementing a solar-powered street lighting system while maintaining its performance and functionality. The solar-powered street lighting system, also known as TALiSMaN-Green allows TALiSMaN to achieve power efficiency and reliability when applying in real-world operation.

Adopting Artificial Intelligence (AI) in street lighting is to introduce adaptive capability and computational intelligence into numerous operative states (Serpen et al., 2013). TALiSMaN-Green implemented AI techniques to estimate energy demand to boost the lighting operation lifetime until next morning. For ISPLC, AI was used to estimate the environmental factors, energy consumption and electricity cost of the streetlight. ISLC also applied the fuzzy control algorithm to classify the dimming of the streetlight.

Although there have been many efforts made to enhance the traditional lighting system, TALiSMaN is shown to be one of the apt schemes for the adaptive street lighting system. The distributed and advanced nature of TALiSMaN combining with high energy efficiency feature makes this lightning scheme outweigh other solutions. Hence, TALiSMaN is the focus of this study to improve the possibility of replacing traditional street lighting system.

2.3 Limitation of TALiSMaN

Even though TALiSMaN provides advanced functionality, however, TALiSMaN is still vulnerable due to data transmission delay. In the predefined area, it requires an instant end-to-end transmission to all the streetlights. Figure 2.2 can further describe the importance of the high precision on data transmission in TALiSMaN. Assume that the distance between streetlight in Figure 2.2 is 30 m apart from each other, a car is travelling with a constant speed of 40km/h through a 120 m of the street, TALiSMaN needs to ensure generated data packets takes about 2 seconds to broadcast across the street, with a distance of 100 m (Lau et al., 2015). The reason is to ensure the streetlights within 100 m surrounding the car is turn on when the car is approaching the next streetlight. The implementation of street lighting system is not useful if the streetlight fails to turn on before the car arrives.

The above-mentioned vulnerability can cause a setback in TALiSMaN, especially in heavy road traffic. During road traffic peak period, the routing protocol applied to assists WSN in TALiSMaN is prone to network congestion and causes packet loss at the rate between 23% to 29% (Lau, 2016). The reason for that is due to constantly sensing and transmitting packets to neighbouring streetlights when traffic volume increases, while overloading the network. Thus, we simulated and evaluated TALiSMaN with various road traffic using StreetlightSim, to generate Figure 2.4 and Figure 2.5, to show the severity of PDR throughout various road traffic volume and the street lighting operation hour, respectively. Figure 2.4 shows that the PDR increases when traffic volume increases, which is comparable to the original author's claims. Figure 2.5 highlights that road traffic peak period during 16:00 to 17:00 and 06:00 to 08:00 have the highest PDR compared to light traffic at 01:00 to 02:00. The results generated will be used as the baseline to benchmark the proposed solution.

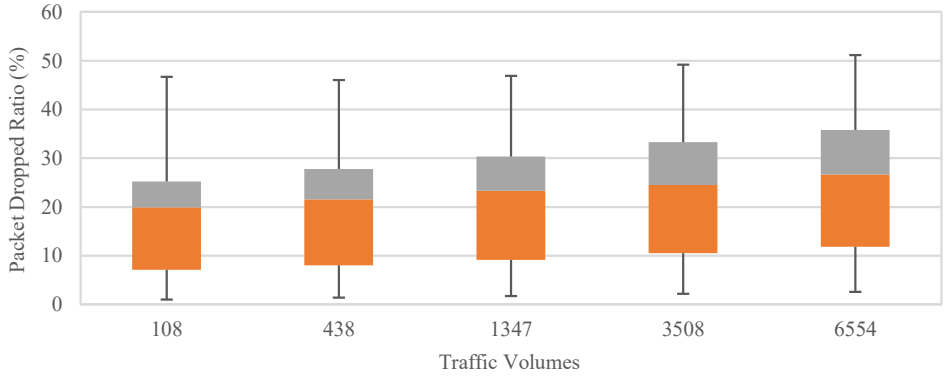


Figure 2.4: The various traffic volumes vs PDR for 100 runs.

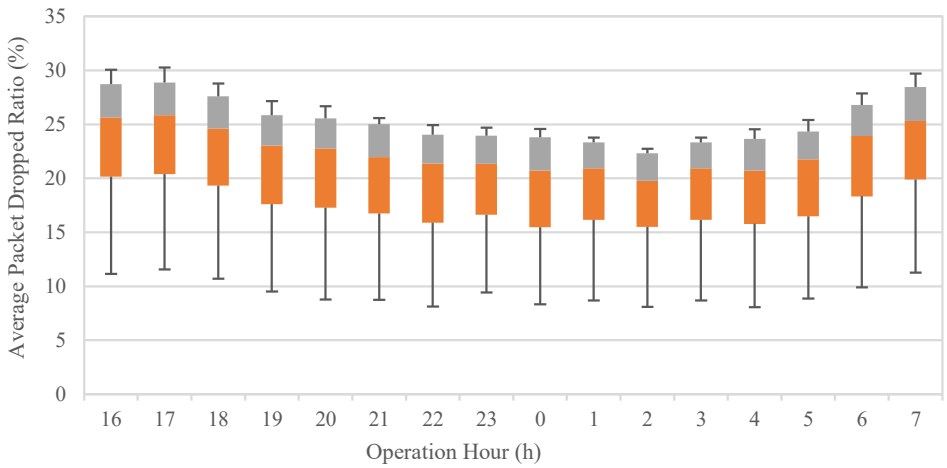


Figure 2.5: The various operation hours vs PDR for 100 runs.

Nevertheless, when neighbouring streetlight did not receive any packet, the streetlight may remain switched on while sensor node constantly senses and transmits packets causing overburden of sensor node and resulting in a misbehaviours of TALiSMaN scheme. If the scheme is unable to ensure the instant and reliable transmission of data to the neighbouring streetlight, the streetlights may not light up or light off whenever it should. Failure to operate as required will be dampening the potential and performance of this scheme, and hence resulting in streetlights slow to respond to the road traffic movements and less efficient in energy consumption. This is crucial as it might affect the utility of TALiSMaN scheme and may cause more harm.

To overcome the limitation of TALiSMaN, existing routing protocols and prediction models are studied to determine the more feasible solution.

2.4 Routing Protocol

Routing protocols are crucial for sensor devices to communicate across the network. A suitably designed routing protocol is necessary as WSNs are required to operate under the conflicting conditions to uphold the reliability of data communications, and packet latency whilst boosts the battery life of the sensors (Bouazzi et al., 2017). A refinement of the routing protocol in TALiSMaN scheme is necessary to resolve the issue of network congestion while maintaining or improving its functionality and performance. Numerous research works have been done to address the problems of routing protocol in WSNs. Hence, the routing protocol adopted in TALiSMaN and the potential routing protocols to resolve the network congestion and packet dropped issues occurred in TALiSMaN during heavy road traffic is further described in the subsection below.

2.4.1 Routing Protocol in TALiSMaN

TALiSMaN uses sensors to detect the presence of pedestrians and motorists, then adjusts the lighting condition of the streetlight to suit road traffic while optimising the use of energy. The scheme works wirelessly, as when a sensor detects road traffic, each streetlight sends a signal to its neighbours; the neighbouring streetlights cooperatively adjust the lights to an ideal lighting condition. The optimum lighting condition for the pedestrian is within 150 m, where the light intensity of the streetlight decreases as it is further from the pedestrian as shown in Figure 2.1; conversely, streetlights within 100 m radius from the detected motorist are completely turned on, as presented in Figure 2.2. Lau et al. (2014) stated that TALiSMaN can maintain the streetlights usefulness while minimizing energy usage by 45% – 98% based on road traffic.

Considering that the sensor does not know the detected users' travel direction, generated data are broadcast to every streetlight surrounding the predefined perimeter for each user type in TALiSMaN scheme. With that, TALiSMaN implemented an updated packet flooding protocol to transmit data to all neighbouring streetlights within the restricted distance. Nodes continuously broadcast their running status to adjacent streetlights at a rate of 2 Hz while the user is still within the sensing range. As to ensure the streetlights within the predefined range obtain the latest operational state to turn on when the user is detected and vice versa.

The generated data packet is sensitive to delay; it requires an instant end-to-end transmission to all the streetlights within the predefined range. With that, TALiSMaN broadcast data packets at a rate of 2 Hz, enabling the minimum detection of passing by road traffic to be at least twice in a cycle. To illustrate the criticality of the functionality of TALiSMaN, i.e., when a car travels with a speed limit of 40 km/h through a 120 m distance street, where every streetlight is approximately 30 m apart from each other, TALiSMaN needs to ensure generated data packets takes less than 10 s to travel 120 m, as the vehicle travels with the speed of 11.11 m/s. This is to ensure the streetlights within 100 m surrounding the car is turned on instantly before the car even arrives at the next streetlight.

The flooding protocol performs flawlessly under light road traffic scenario; but network congestion occurs during a heavy road traffic scenario, causing packet loss with the rate of 23% to 29%. The generated data is time-sensitive, and it must be transmitted with minimal delay to neighbouring streetlights within the restricted distance. If TALiSMaN cannot ensure the instant transmission of information, it will diminish the usefulness of

having street lighting and performance of the scheme, resulting in slow response of streetlights to road traffic movements and worsen energy wastage.

2.4.2 Potential Routing Protocol for TALiSMaN

Firstly, TALiSMaN aims to achieve energy efficiency to resolve the drastic drainage of energy during sensing and transmitting process of sensor node at the heavy road traffic period since battery only offers limited energy storage. Due to the used battery and solar power in TALiSMaN, it limits the energy usage of streetlight for a day as to reserve energy to allow the streetlight to turn on for the next day.

Secondly, the streetlights in TALiSMaN are clustered into segments based on the different road patterns, i.e., linear pattern, radical pattern, rectangular pattern, T-junction, 3-way intersection, etc. By clustering into different segments, each segment can have its network control mechanism to boost the performance of TALiSMaN. To illustrate, during heavy road traffic hour that is 6-7 pm, the streetlights at the t-intersection can remain turned on while streetlights at the linear path perform normal TALiSMaN operation.

Thirdly, congestion control routing protocols are chosen to handle network congestion and packet loss in TALiSMaN. As mentioned above, heavy road traffic causes constant data packet transmission that could lead to packet loss and network congestion, while exhausting the WSNs at that specific area. When sensor nodes fail to perform, it can diminish the purpose of TALiSMaN and burden TALiSMaN from fully utilise its full potential.

Thus, the reviewed routing protocols are described and categorised into three categories, include energy-efficient routing protocols, cluster and grid-based routing protocols, and congestion detection and control routing protocol in the subsection below.

2.4.3 Comparison of Reviewed Routing Protocols

The routing protocols and the architecture described in the previous sections have their advantages and limitations. Choosing the appropriate routing protocol is undeniably challenging and should consider factors like network volume, network lifetime, packet latency, packet drop, and load balancing, etc.

Network volume would affect the performance of routing protocols in TALiSMaN. The routing protocols can perform effectively without disruptions when the network is small. As network volume increases, more nodes are engaged in the network operation, thus increasing network data traffic, and producing huge network overhead, which could lead to packet latency or even packet drop.

The next factor affecting the performance of TALiSMaN is energy constraint, which happens when implementing with off-grid power supply. As mentioned above, the increase in overhead is due to high data traffic, the lights may fail to receive signal to turn off, which causes high energy consumption in WSNs. Since the battery used in off-grid scheme is very bulky and heavy to carry around, it is not feasible to constantly change the batteries once it fails. It is crucial to extend the network lifetime as to ensure TALiSMaN scheme can perform effectively.

Load distribution is another element influencing the performance of routing protocols. When network volume increases, the network traffic and overhead increase,

causing latency and buffer overflow, leading to packet congestion. Owing to that, proper load distribution management is vital to ensure efficient use of the buffer capacity of each sensor node to avoid network congestion. Congestion aware routing protocol proposed by Park et al. (2015), Bouazzi et al. (2017) and Liu et al. (2017) periodically check the buffer size before transmitting data packets to the next nodes in WSNs. However, the reviewed routing has its limitations on the time-critical, linear street lighting network.

From the factors mentioned previously and the unique requirements of TALiSMaN, none of the reviewed routing protocols, can fully satisfy the performance requirements for TALiSMaN scheme. Table 2.1 summarised the attributes, strengths and drawbacks of the protocols reviewed in this paper. Based on the papers reviewed, the common issue of network congestion, packet drop, and the high energy consumption is caused by extensive used of WSNs causing a heavy transfer of data, mass multimedia data, multiple nodes send packets to the same receiving node simultaneously, long packet communication distance, and directs ACKs per receiver leads to ACK storm. In short, the leading source for affecting the performance of the WSNs is the massive network traffic load. Without proper management of the network traffic, the network can easily be congested, causing network packets to drop and eventually misbehaviours of the application, which depending on the underlying communication protocol. The challenges of WSNs are to maintain timely and reliable data transmission. The critical review based on the papers reviewed are listed below:

i. Majority of the existing routing scheme required to transmit packets to the base station, which is not sensible to TALiSMaN as it is distributed in nature.

ii. The reviewed scheme set a priority level for the packets and transmit based on the congestion level detected.

iii. Some of the existing reviewed schemes utilised clustering and congestion detection feature to establish a new route for the source node to avoid packet drop. It is not feasible for linear street lighting, as each node must receive the packet transmitted by the neighbour node.

Table 2.1: Summary of reviewed routing protocol

Main Goal	Protocols	Characteristics	Strength	Drawbacks	Justification
Energy efficient	EDR	Query-driven and event-driven applications.	• Reduce overhead, one hop transmission. • Require less memory with a short and reliable path. • Balance energy used between nodes. • Limit redundant and unnecessary response.	• Requires more time to categories data, check data type before transmission and check data duplication through aggregation. • When majority priority data occur, data might need to travel through alternative paths (longer path)	• Dependent on the base station • The alternative path is not feasible for linear street lighting
Energy-efficient and reliable	REEV BF	Local flooding by packets, followed by the adaptive selection mechanism.	• Reduce data transmission by allowing only optimal node forwards packet. • Suitable for shallow water acoustic network	• Multiple nodes receive repeated packet transmission. • Not universally applicable • RF front-end needs to emit more energy to send the packet	• Prove existing routing protocol is not universally applicable. • Base station dependent
Energy-efficient and scalable	Bee-Sensor-C	Dynamic clustering scheme for parallel data transmission.	• Well distribution of workload. • Dynamic clustering scheme • Multiple paths selection • Multi-cluster setup support	• Requires forward and backward scout to search for a sink node from CH. • Nodes within overlapping clusters may be overload causing wastage of energy	• Packets need to travel twice to complete a task.
Ensure link quality	MCR	Use Random Walk theory to find the best path based on DBM.	• Reliable routing path • Robust routing discovery • Discover and record alternative routes as for other available destination	• REQ packet floods all nodes with an unlimited hop that results in excess communication overhead. • May have low performance when using in poor link quality	• Discovery of the ideal routing path is not feasible for linear street lighting and can lengthen the transmission time
Energy-efficient, network lifetime	P-SEP	The categorised energy level of sensors for CH nomination.	• Prolong network lifetime. • Improve network stability and packet transmission rate	• Increase in network traffic may cause exhaustion of nodes closer to CHs. • Requires time to re-setup for each round	• Does not require a CH role in the linear street lighting network
Routing hole, network lifetime	OHCR and OHA	Relink disjoint path while avoid topology restructure.	• Reconnect disjoint nodes. • Minimised energy consumption during topology transformation	• If a dangling hole is located further from base station, it may require more energy and network resources for data communication	• Computational overhead as it requires a constant check for topology reformation
Load balance, network lifetime	EDAL	Discover the minimal energy cost transmission path with low latency.	• Reduce computation complexity. • Easily scales into a large-scale network	• Algorithm overhead • Larger network size takes longer time to finish the computation	• Not feasible for time-critical system • Computational cost • High power consumption
Energy efficient	SIF	Apply fuzzy inference method to predict eligible CH.	• Balance cluster and load distribution • Ensure general applicability of routing protocol	• Extensive use of WSN may cause exhaustion to nodes surrounding CHs, leading to network premature end	• Election of eligible CH may not be feasible for the linear street lighting system

Table 2.1 continued

Energy-efficient and data delivery	AECR	Balance stability of clusters structure with minimum overhead.	• Least computational overheads • Optimised relay nodes • Reliable routing path • Balance load distribution	• Requires memory to keep track of routing table. • When all potential CHs deplete, nodes at the further position would consume more energy during data transmission.	• Not feasible as the operation of TALiSMaN is event-driven. • Base station dependent
Mitigate congestion, network lifetime	EBZ	Re-establish new zone and route based on congestion level.	• Quick cluster formation • The lightweight process to choose ZL. • Avoid congestion. • Efficient path selection	• Computational complexity • Communication overhead	• New route establishment is not relevant for the street lighting scheme
Reduce energy usage of nodes closer to CHs	EEDCF	Using inference system to elect CHs based on several factors.	• Improves quality of CH candidate. • Balance load distribution inside the cluster • Extend the lifecycle of WSNs	• When database increase, more energy is required to analyse and predict the eligible CHs. • Resource overheard to determine an alternative path	• Not feasible in the critical system as evaluation requires time. • Not suitable for a linear street lighting system
Energy efficient, QoS-aware	QHCR	Provide a dedicated path for real-time traffic.	• Multipath communication provides fault tolerance, load balancing, reliability and reduces end-to-end delay.	• Constant topology changes and exchange topology updates in large scale network may waste energy resources	• The alternative path is not feasible for a linear street lighting scheme
Balance energy used	BPA-CRP	Breaks network into layers and clusters.	• Balance load distribution • Reduce communication and control overhead. • Prolong the network lifetime	• Increase in the sensor field size reduces the network lifetime as distance towards the base station increases	• Dependent on sinks node • Not suitable for large scale network
Reduce packet latency	ECCM	Reduce latency by prioritizing data packets.	• Improve the transmission rate through traffic control. • Minimise cross-sectional latency	• When huge multimedia data transmission occurs, exhaustion of nodes might still occur. • Congestion detection and notification may deplete the energy more quickly	• The alternative path is not feasible for the linear street lighting scheme
Minimise packet drops	CA-GPCR	Apply congestion aware procedure to select next best hop.	• CA-GPCR can choose the most suitable next node while preventing the problem of buffer congestion. • Higher packet delivery ratio • Lower end-to-end delay time	• When network traffic increase, the huge processing power is required to select the next best neighbour	• The alternative path is not feasible for the linear street lighting scheme
Energy-efficient, reduce packet drops	Fuzzy logic in CSMA /CA	Apply fuzzy logic on priority queuing and transmission rate management.	• Effectively manage resources and control data transmission • Decrease packet drop. • Robust fuzzy rule	• When every packet is a high priority, network congestion might still occur. • Consumed more energy for higher traffic loads	• The alternative path is not feasible for linear street lighting. • Consumed more energy for heavy traffic loads
Load balance, reduce packet loss	QU-RPL	Select an eligible parent node to avoid congestion.	• Load balance by managing queue usage. • Improve end-to-end packet delivery	• Requires more computation power and resources to handle the constant change of parent node. • Resource overhead for run-time computation of alternative paths	• Not suitable for time-critical application as data latency may occur during the selection of parent node
Reduce packet loss	IR-DRA	Send queue size of forwarding node to a neighbour.	• Ensure reliable communication. • Enhance the packet delivery ratio and end-to-end delay	• Sending control message may cause network overhead	• Not suitable for time-critical application as data latency may occur during the selection of parent node

Table 2.1 continued

Reduce network overhead	CoLBA	Use the predictive method to improve the transmission of the control message.	• Avoid queue overflow. • Better end-to-end delivery ratio • Reduce packet loss	• Sending control packets for congestion notification may cause network overhead. • Requires more resources to calculate the alternative path	• The alternative path is not feasible for linear street lighting
Reduce network congestion	Mobile CC	Provide disjoint and direct paths to resolve congestion.	• Reduce end-to-end delay and packet drop for direct MobileCC	• Requires more resources to calculate the alternative path.	• The alternative path is not feasible for linear street lighting

2.4.4 Discussion on Routing Protocol

This study surveyed the recent research approaches in the development of routing protocol for WSNs while considering the characteristic of the solution to determine its applicability in TALiSMaN. The reviewed routing protocols are classified based on the technique used, its motivation, and characteristic. With that, this study can determine the potential techniques to address the network flooding experienced by TALiSMaN.

Most of the reviewed techniques provide an alternative path or dedicated path either for delay-sensitive or normal data packet transmission when congestion in buffer queue is detected. However, the alternative or dedicated path option is not suitable for TALiSMaN as all nodes attached to the adjacent streetlights are required to receive the sensed data and operate the streetlights accordingly. Moreover, as most of the streetlights are planned along the road forming a linear-alike network topology, selections of CHs or forwarders' role in TALiSMaN is unnecessary. Nevertheless, clustering technique is useful to TALiSMaN, like the categorisation of the different types of roads into a cluster to ensure proper management of the network to avoid network congestion.

Most of the reviewed papers adopted centralised system concept where data packet transmission often occurred from sensing nodes and relayed to a base station or sink node. Hence, factors such as communication distance, queue length, energy residual of the source node, the average remaining energy of the neighbour nodes, the total neighbour nodes, etc. need to be considered to ensure the reliability network communication with minimum delay and packet loss. TALiSMaN is a distributed network system where every sensor node generates, broadcasts, receives, relays and processes sensed data without implementing a base station. Thus, the total amount of data transmission is lower compared to those with base station, and factors considered to ensure reliable network path mentioned above are not applicable or sensible to TALiSMaN.

Regarding congestion control scheme, some of the routing protocols employed priority level applied to the data packets before data transmission, to ensure high priority packet can be transmitted through the shortest path with less network overhead (Amjad et al., 2017), (Bouazzi et al., 2017) and (Park et al., 2015). By applying the prioritised-based technique according to different network traffic pattern on TALiSMaN could avoid exhaustion of nodes, routing hole or premature end of network lifetime. However, these techniques require the use of extra control messages to periodically report the queue length and sending rate of each node are not feasible to TALiSMaN, because the extra control message will further increase the network traffic which is already congested. Reason for that is when transmission of control messages elevated throughout the network, portion of the bandwidth may be lost, that impacted the data throughput.

2.5 Prediction Model

Other than implementing the routing protocol, there have been some other attempts to tackle network congestion. One of the methods is applying the prediction model to forecast the situation of real-time data transmission in a network, then determine the action to prevent the happening of network congestion. Another challenge arises, which is to perform a model selection that best suited for the TALiSMaN scheme since there are various prediction models to opt for. Theoretically, an advance framework like Artificial Intelligence, Neural Network, shall be straight away become the right choice for this study. However, the learning process of these advance framework leads to time-consuming in model development, compared to simpler statistical model structures (Karlaftis & Vlahogianni, 2011). This section discusses the various techniques or algorithms of predictions and their respecting use case.

2.5.1 High Complexity Online Predictors

A statistical model such as Auto Regressive Integrated Moving Average (ARIMA) has been quite popular around as a predictive model for various domains, especially transportation research in Kumar et al. (2013), Das et al. (2015) and Moghimi et al. (2017). This method is a combination of autoregressive (AR) and moving average (MA) hence become ARMA. It is further extended to become ARIMA where the "I" stands for "integrated" representing the difference of data value between the current value and past value. Mehdi et al. (2019) realised the importance of high accuracy in traffic prediction for resource management in cloud computing. The ARIMA was apt to predict short term traffic conditions but to gain accurate results it required a huge amount of historical data which is not ideal for a limited available memory on a WSN node.

Artificial Intelligent models such as Machine Learning and Deep Learning are some buzzwords these days. Machine Learning is a subset of artificial intelligence that can create and perform the algorithm itself without human intervention (Jiang et al., 2017). Deep learning is a subset of Machine Learning that consist of numerous layers of algorithms, also known as artificial neural networks (Levine et al., 2019). (Wu et al., 2004) proposed a machine-learning technique, namely support vector machine (SVM) (Polson & Scott, 2011) to predict vehicle travel times. (Quek et al., 2006) suggested a neural network incorporate with a fuzzy method to manage non-linear data in traffic data. Zhao et al. (2017) adopted Long Short-Term Memory Neural Network (LSTM) for travel prediction by utilising temporal-spatial correlation techniques through a two-dimensional network. The cost of training these models is computationally expensive, even though frequent updating is being prohibitive (Kamarianakis et al., 2012). While these approaches can perform well, there is one drawback that is these models are technically difficult to implement on large scale networks.

2.5.2 Low Complexity Online Predictors

Moving average is a data smoothing method that uses time-series data to predict the future trend of the data. There are various forms of moving average, but this study will look at the three basic forms of moving average, which are simple moving average (SMA), weighted moving average (WMA) and exponential moving average (EMA).

The simple moving average (SMA) is frequently used in time series forecasting (Johnston et al., 1999). This method calculates the average of time series data and make use the result to predict the upcoming trend. The reliability of this method is depending on the size of the previous record. The new value of “average” will replace the previous value of

"average", and this is causing a problem that it will always lag behind the actual data, although the results are easier to produce (Hussain & Sohaib, 2019). As shown in the Equation 2.3, the calculation of refined SMA is by taking the average of previous n weeks of day d road traffic data ε_d at time t. The refined SMA is inspired by (Investopedia, 2020), where the calculation to estimate $\acute{\varepsilon}(t)$ is given by Equation 2.3:

$$\acute{\varepsilon}(t) = \frac{\sum_{d=1}^{n} \varepsilon_d}{n} \qquad \text{Equation 2.3}$$

Where:

$\acute{\varepsilon}(t)$ = Forecast of traffic volume at time t of a day using SMA

d = Day of the week

ε_d = Road traffic volume of previous d day of the week at time t

n = The number of historical data in days

The weighted moving average (WMA) works slightly different than SMA. It estimates the future values by taking the sum of each multiplication of ε_d data with a weighting factor. The sum of these weights is equivalent to 1 or 100%. The WMA puts more weight on the most recent data rather than older data. Unlike SMA, where does not have any weighing factor in the historical data. The impact of the weighing factor of WMA consistently decreases from recent data until it reaches the initial observation of data (Hussain & Sohaib, 2019). Many analysts believe WMA will produce a better result than SMA as it can respond to any changes in future data due to WMA focus more on the recent data. The refined WMA is inspired by Corporate Finance Institute (n.d.), where the calculation to estimate $\acute{\varepsilon}(t)$ is given by Equation 2.4:

$$\acute{\varepsilon}(t) = \frac{\sum_{d=1}^{n}(n - d + 1)\,\varepsilon_d}{\alpha} \qquad \text{Equation 2.4}$$

Where:

$\acute{\varepsilon}(t)$ = Forecast of traffic volume at time t of a day using WMA

$\alpha = \frac{n(1+n)}{2}$, Weighting factor (Corporate Finance Institute, n.d.)

d = Day of the week

ε_d = Road traffic volume of previous d day of the week at time t

n = The number of historical data in days

The exponential moving average (EMA) uses a weighting factor that decreases exponentially for each historical data point (Raiyn & Toledo, 2014). This is what makes it different from WMA by emphasizing the recent value of data while not entirely diminishing the value of older data. According to Lamontagne et al. (2016), EMA is more accurate and robust when compared to SMA. The accuracy of EMA relies on the weighting factor of the recent data and the prediction length (StockCharts, n.d.). The EMA is a forecasting method that assigns unequal weight to the time series data. The unequal weight is achieved by using one or more smoothing parameter, which determines how much weight is assigned to each data. The advantage of EMA is that it is very versatile, it can provide better forecasting in a wide variety of applications. The dependence of EMA on computing requirements and data storage is minimal, which is why it is more suitable for real-time application. The refined EMA is inspired by StockCharts (n.d.), where the calculation to estimate $\acute{\varepsilon}(t)$ is given by Equation 2.5:

$$\acute{\varepsilon}(t) = \alpha * \varepsilon_{d-1} + (1 - \alpha) * \acute{\varepsilon}_{d-1} \qquad \text{Equation 2.5}$$

Where:

$\acute{\varepsilon}(t)$ = Forecast of traffic volume at time t of a day using EMA

$\alpha = \frac{2}{1+n}$, Weighting factor (StockCharts, n.d.)

d = Day of the week

ε_d = Road traffic volume of previous d day of the week at time t

n = The number of historical data in days

$\acute{\varepsilon}_{d-1}$ = Forecast of previous d day of the week road traffic at time t

2.5.3 Discussion on Prediction Model

The ARIMA is a more advanced version of the Statistical Model; it combines the technique of Auto Regression and Moving Average. However, it is not a suitable solution in this study as the computing resource is limited for TALiSMaN that operating with a WSN. Thus, the weightage on deciding the prediction model should give to efficiency over performance. Whereas Artificial Intelligence, other than heavy taxing on a computing resource, is far too complex to implement on TALiSMaN.

Network congestion in the networked street lighting system causes an increase in packet drop and network latency. Consequently, the streetlight is unable to utilise the full potential of the TALiSMaN scheme if it fails or late to receive the signal to switch on or off. A streetlight is practically useless when it is unable to switch on in the dark. On the contrary, streetlight continuously turns on throughout the night can cause excessive energy

consumption and prompt to financial burden. To tackle this issue in the networked streetlight system, a non-heavy computation prediction model to mitigate network congestion and packet dropped need to be adopted.

2.6 Summary

This chapter begins with reviewing networked street lighting schemes, which includes TALiSMaN and TALiSMaN-Green, ISPLC, SHLMS, ISLC, and ASLS approach. TALiSMaN has been chosen to proceed further in this study due to its advancement, distributed in design, and able to perform dynamically and remotely without depending on human intervention. However, there is a limitation in this scheme where it is experiencing the issue of network congestion because of the heavy transmission of data during the operation. At first, the idea of implementing an improved routing protocol has the potential to resolve the issue. Based on the reviewed routing protocols, it is found that the majority of the existing routing schemes are not suitable for linear topology and the concept of having base station or sink node is not applicable to TALiSMaN. The centralised network system is not sensible as it might generate duplication of unnecessary data.

With these findings in mind, the study is then further exploring the possibility of adopting predictive model in a TALiSMaN scheme to overcome the network congestion issue. The idea is to make use of the prediction model to anticipate the future road traffic condition. Then TALiSMaN broadcasts the message to toggle each streetlight, according to the prediction result. There are complex online predictors such as ARIMA and machine learning approaches available for the road traffic prediction. According to the literature review, these prediction models could provide effective results, but not an ideal implementation for TALiSMaN scenario. This was due to the computation power required

of the prediction process. This has led to the adoption of low complex online predictors such as SMA, WMA and EMA.

CHAPTER 3

REAL-TIME TRAFFIC PREDICTION MODEL FOR TALISMAN

3.1 Introduction

In Section 2.2, a few networked street lighting schemes were discussed, and TALiSMaN was found to be the most suitable to be adopted in this study. However, there are some limitations in TALiSMaN during road traffic peak period. To overcome the limitations, various routing protocols have been reviewed, and based on the observation these limitations occur during specific road traffic conditions. Owing to that, if these conditions can be forecasted, then counter measure can be positioned to prevent the occurrence of packet flooding. Thus, this chapter presents the implementation of the prediction techniques into TALiSMaN scheme. This chapter describes the proposed solution, followed by the steps to obtain a feasible prediction technique and the description for the various functionalities of the proposed schemes.

3.2 Proposed Solution

To address the challenges of TALiSMaN operating during road traffic peak period, TALiSMaN with predictive control is proposed. The purpose of the scheme is to ensure the street lighting can turn on as intended, even during rush hour, thereby achieving consistent usefulness throughout the night. The concept of this scheme is to adjust the lighting operation based on road traffic conditions adaptively.

Figure 3.1 illustrates a detailed system component of TALiSMaN with predictive control. The proposed system consists of the Predictive Control module and inherits the modules from TALiSMaN scheme that includes the Lighting Control and TALiSMaN

modules. The TALiSMaN module observes the presence of road traffic and computes the lighting requirement based on detected road traffic information by the sensors. The Lighting Control manages the lighting condition based on the computed requirement obtained from TALiSMaN module. The Predictive Control module consists of four phases, namely data collection, prediction, detection, and control phase. The Traffic Logger aggregates the historical road traffic data over a time interval for road traffic congestion threshold estimation and prediction purpose. The Congestion Threshold Estimator calculates the road traffic congestion threshold value, φ for congestion classification purpose. The Road Traffic Predictor estimates the road traffic, $\acute{\varepsilon}(t)$ at timeslot, ϑ. The Congestion Classifier categorise the road traffic condition of $\acute{\varepsilon}(t)$ based on φ, then manages the packet propagation status and lighting requirement based on road traffic condition through TALiSMaN.

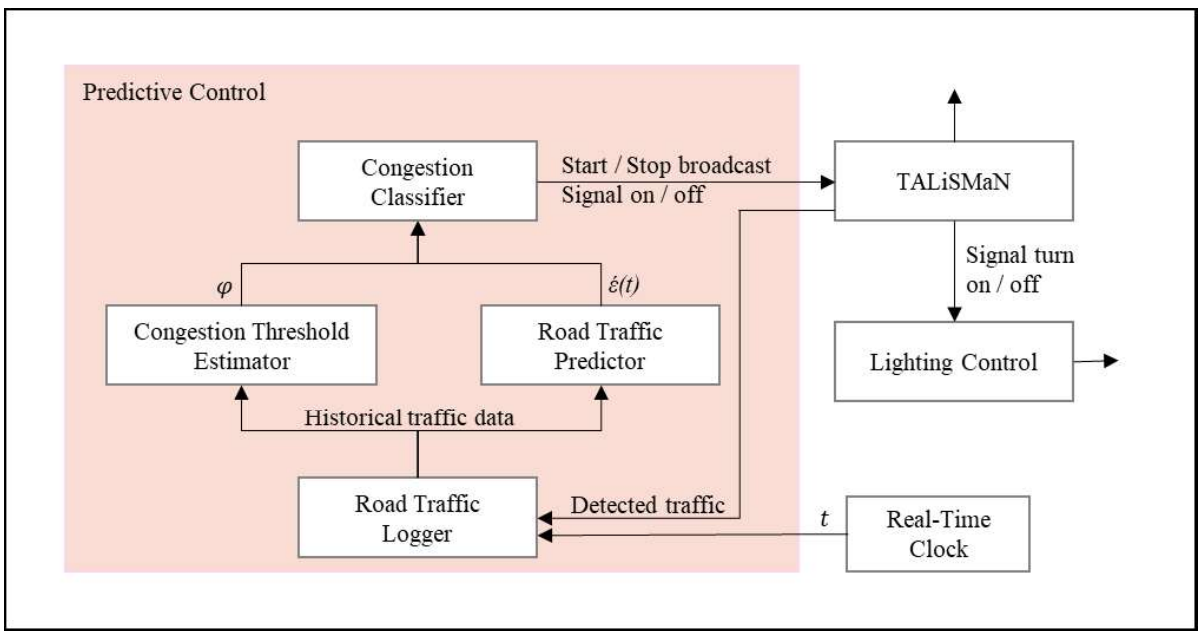


Figure 3.1: System overview of TALiSMaN with predictive control.

To predict $\acute{\varepsilon}(t)$, the street lighting operation hour is divided into equal-sized timeslots, ϑ based on the selected prediction windows, w. The total road traffic, ε_d for

each ϑ is recorded and used to forecast road traffic, $\acute{\varepsilon}_d$ in future timeslots. The ε_d for a day is used to calculate the φ. Both φ and $\acute{\varepsilon}(t)$ are compared to determine the road traffic condition. If heavy road traffic condition for ϑ is detected, the streetlight will receive signal to turn on street lighting and stop broadcasting until next ϑ. Since the focus of this research is ease network congestion and packet dropped issues during heavy traffic flow, the street lighting operation proceed as defined in TALiSMaN scheme when light traffic occurs at ϑ.

In short, these functions require:

i. Knowledge of the current time, t

ii. Prediction of the road traffic for a day at time t, $\acute{\varepsilon}(t)$ when TALiSMaN requests traffic condition.

iii. Estimation of the road traffic threshold for a day, φ to determine the road traffic peak period.

The following subsections emphasise on (ii) and (iii) listed above. Since streetlights implementing TALiSMaN with predictive control is powered by WSN, thus, it is assumed that t is synchronised in the network and is accessible to TALiSMaN with predictive control.

3.3 Road Traffic Predictor

Based on Section 2.5, moving average prediction model is chosen to further examine in this study, as it provides low complexity, requires less resource, and perform predictive analysis in real-time. Moving average is a smoothing method that forecasts future values that heavily depends on historical data. This study explores three moving average algorithms to plug and play with the TALiSMaN scheme to determine which is the most resource-efficient

method and yet most effective in reducing the network congestion. These algorithms include Simple Moving Average (SMA) (Hansun, 2013), Exponential Moving Average (EMA) (Holt, 2004) and Weighted Moving Average (WMA) (Zhuang et al., 2007).

Example to predict road traffic volume for 8.20 pm on Monday, if the prediction length, n is 7 days, then the road traffic data of 7 previous Mondays at 8.20 pm is used for estimation. If the prediction window, w is 20 minutes, then the streetlight operation hours will be split into equal-sized of 20 minutes apart for each timeslot, ϑ to perform prediction. The selected prediction model and prediction parameters based on Section 3.6 are adopted for simulation and evaluation in Chapter 4.

3.4 Congestion Threshold Estimator

The categorisation of predicted traffic data utilises the road traffic congestion threshold value, φ as a metric to determine a congestion situation. The calculation for φ is compute using the average value of the road traffic data on a specific day from previous week. Before the prediction process occur, every sensor node will store up to $n = 7$ of historical road traffic dataset (as obtained from Section 3.6.4).

For instance, the first step is determining the operating hours of the street lighting in a day then perform data collection. Typically, the operation hour of a street lighting in a day starts from 16:00 until the next day 08:00, as shown in Figure 3.2. The φ is obtained by taking the average value of the road traffic data in a day as shown in Figure 3.2, where the total road traffic data is 1720 vehicles and ϑ is 72 timeslots, thus φ is 24 vehicles. After the prediction is performed, $\acute{\varepsilon}(t)$ will be compared with the average value obtained previously (which is 24 as mentioned above). Predicted traffic data greater than the φ (i.e., $\acute{\varepsilon}(t) > 24$)

is categorise as congested, while predicted data lesser than φ ($\acute{\varepsilon}(t) < 24$) is categorise as non-congested period. The equation of φ is given by Equation 3.1:

$$\varphi = \frac{\sum_{t=1}^{\vartheta} \varepsilon_t}{\vartheta} \qquad \text{Equation 3.1}$$

Where:

φ = road traffic congestion threshold value for previous d day

ε_t = road traffic volume of previous d day of the week

ϑ = total number of timeslots

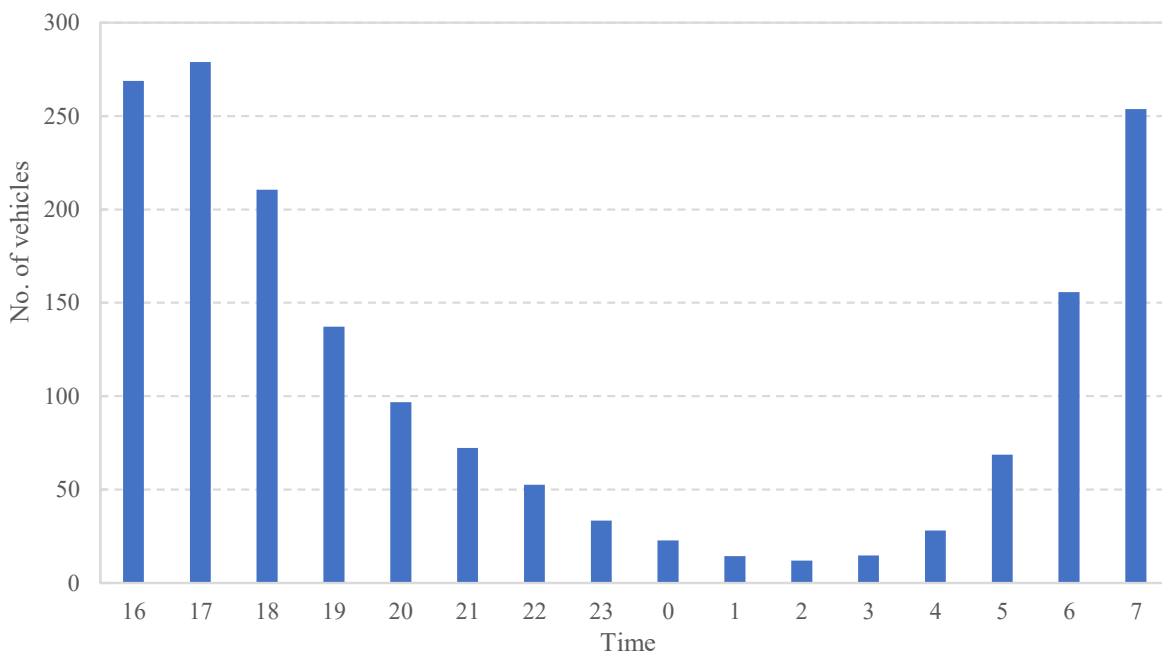


Figure 3.2: The simulation results of Monday vehicle distribution generated by StreetlightSim with 3508 road traffic per day.

3.5 Congestion Classifier

The issues of network congestion and packets drop during road traffic peak period cause interruption to the operation of TALiSMaN as streetlights are unable to turn on or off accordingly and such interruption can degrade its usefulness. Owing to that, this subsection intends to address the issues by providing forecast of the road traffic congestion condition, then manage data broadcast, and deliver a consistent streetlight usefulness throughout the streetlight operation hours.

To illustrate, assuming prediction for ϑ_1 (16:20 to 16:40) is performed five seconds before ϑ_1 when $w = 20$ minutes, and the $\acute{\varepsilon}(t)$ indicated road traffic congestion (heavy traffic flow) for ϑ_1. Then a request is sent to TALiSMaN to stop the packet propagation for every sensor node and signal the streetlights to turn on at ϑ_1 for 20 minutes. The prediction process will continue at 16:35 to predict for ϑ_2 (16:40 to 15:00). If the $\acute{\varepsilon}(t)$ is lower than the φ and denoted as no congestion, then packet propagation and lighting operation will proceed as intended in TALiSMaN for ϑ_2.

3.6 Selection of Real-Time Online Prediction Model

Before delving into which prediction method is feasible for TALiSMaN, several prediction parameters are considered in forecasting the road traffic. These prediction parameters include the simulation iteration requirement (Section 3.6.1), the historical data aggregation (Section 3.6.2), the prediction windows, w (Section 3.6.3), and the prediction lengths, n (Section 3.6.4) for each of the moving average methods.

To obtain the prediction parameters, the simulation of TALiSMaN scheme is set to run over a period of 200 weeks, using the linear network topology with 12 streetlights distributed across a residential street, as shown in Figure 4.1. The simulated streetlights will

operate from 16:00 to 08:00 the next day, with 3508 (Lau et al., 2014) road traffic per day, to test and validate the factors mentioned above.

Note that there is no real data used as the simulated traffic pattern is based on the traffic distribution profile adopted from Southampton City Council (European Platform on Mobility Management, n.d.). The generated road traffic data is adequate and equivalent to real life road traffic scenario, as the car is randomly injected at any point of the road, either moving to the left or right. The car is also randomly added at any time based on the traffic ratio predefined in the road distribution profile for a specific time.

After obtaining the parameters to assess all three predictors, root mean square error (RMSE) (Chai & Draxler, 2014) is applied to evaluate the accuracy of each method in predicting $\acute{\varepsilon}(t)$ of day d at time t. The equation of RMSE is given by Equation 3.2:

$$RMSE = \sqrt{\left(n^{-1}\sum_{d=1}^{n}(\acute{\varepsilon}_d - \varepsilon_d)^2\right)} \qquad \text{Equation 3.2}$$

Where:

$\acute{\varepsilon}_d$ = Forecast of road traffic data at period t of a day

ε_d = Actual road traffic data generated by TALiSMaN scheme at period t

n = The number of historical data in days

3.6.1 Determine the Simulation Iteration Requirement

This subsection aims to determine the adequate number of simulation iteration to avoid unnecessary simulation iteration when evaluating TALiSMaN scheme. Figure 3.3

shows the result of average PDR for all lamps at operation hour 17:00 across the simulation iteration sets from 10 to 200, with step of 10. Operation hour 17:00 to 18:00 is chosen because it has the highest number of traffic occupying the road based on Figure 3.4 throughout the street lighting operation hours. Based on the simulation result, the PDR shows consistent results for all considered simulation iteration sets, with an average PDR ranging from 25.2% to 25.3%. However, simulation iteration sets of 10 is chosen as it has the least difference between the minimum and maximum PDR with 48.5%, whereas the rest of the considered iteration sets is among the range of 49.5% to 50%. Since the difference of simulation iteration sets of 10 is insignificant compared to iteration sets of 20 to 200, thus 10 iteration sets are adopted for the simulation and evaluation of the following prediction parameters and the proposed scheme in the following chapter, as it is adequate to produce an accurate result.

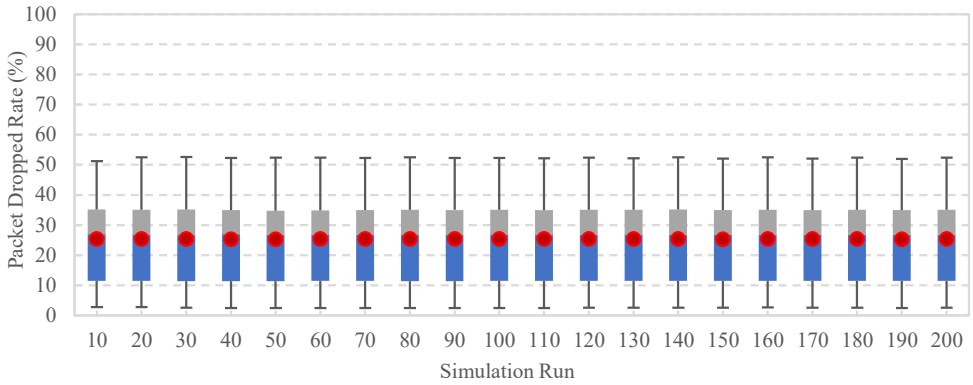


Figure 3.3: The average PDR across the 200 runs.

3.6.2 History Data Aggregation

Figure 3.4 shows the average weekly road traffic profiles throughout a year adopted from Southampton City Council (European Platform on Mobility Management, n.d.). The road traffic profile from 16:00 to 08:00 throughout the week are adopted, to represent road

traffic volume during streetlight operating hours for this research. Since the road traffic profiles indicate perceptible trends throughout the days of week, thus it is realistic to assume historical road traffic data from previous week of the same day and time can provide a more accurate prediction than previous day data. For instance, when predicting for time 17:00 on Monday, assuming n is two, then the traffic data at time 17:00 from two previous Monday is expected. Thus, the simulated road traffic data will be accumulated into weekly format for simulation and evaluation of the following subsections.

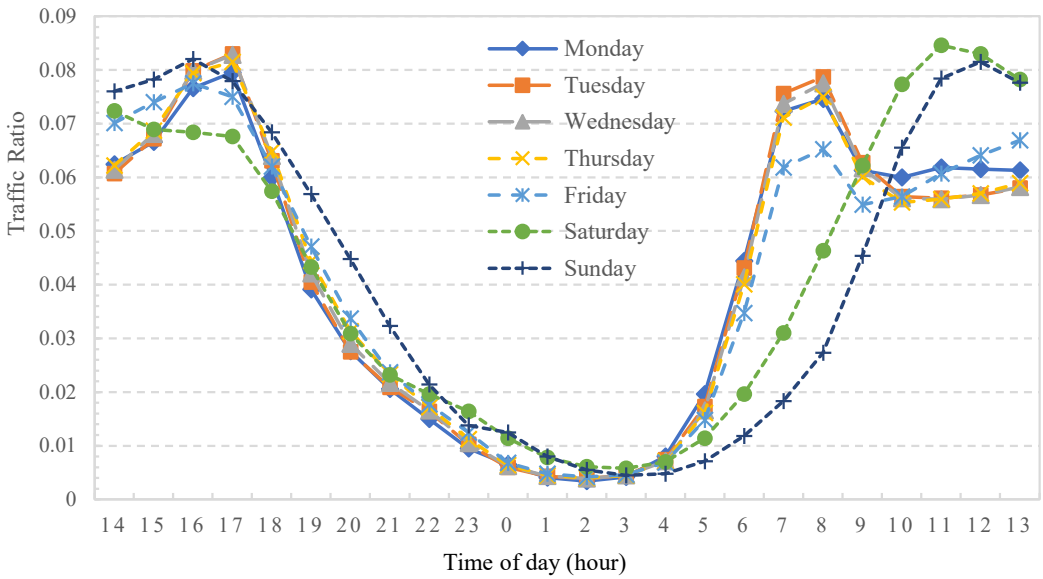


Figure 3.4: Road traffic distribution ratio throughout the week (European Platform on Mobility Management, n.d.).

3.6.3 Determination of Prediction Window

The role of w is to determine frequency of the occurrence of prediction that yield the least prediction error. In TALiSMaN, the traffic volume is recorded every second, these data are then pre-processed into groups based on the equal-sized prediction window time interval. The prediction windows, $W = \{5, 10, 20, 30\}$ in minute are considered for this work. For

instance, if $w = 5$, then there is one record for each five minutes timeslot, one hour will have 12 timeslots and one day will have 288 timeslots, the same process applies to other w values. To obtain the total timeslots, ϑ for each w, the equation is given by Equation 3.3:

$$\vartheta = \frac{24\ hours \times 60\ mins}{w} \qquad \text{Equation 3.3}$$

Where:

ϑ = total timeslot of w throughout the operation hour in a day

w = prediction window

To ease the simulation models and considering the traffic pattern as shown in Figure 3.4, was collected hourly, those prediction windows without division reminder in an hour are adopted in this research work, as such $W = \{5, 10, 20, 30\}$. If $w = 25$ minutes is chosen, then the prediction cycle may end at 07:45, and the next timeslot will never be reached if simulations are evaluated hourly. This may cause unnecessary complexity in the simulation models. Note that, $w = 1$ is not considered as to avoid constant traffic prediction for short prediction time interval, that might cause discomfort to road traffic due to constant blinking of streetlights. The $w = 60$ minutes is not considered because the prediction time interval might be too long will expose to unwanted event, such as accident. Since the traffic profile applied in this study does not consider the event of accident, hence, the prediction windows, $W = \{5, 10, 20, 30\}$ are more favourable.

The traffic generated by TALiSMaN is tested with $W = \{5, 10, 20, 30\}$ for SMA, EMA and WMA using 10 different sets of simulation scenarios from TALiSMaN scheme in linear network topology. Based on the RMSE distribution as shown in Figure 3.5, all

considered predictors indicate improvement as the w value increases. All selected predictors can forecast more accurate traffic when historical traffic data is recorded within a longer period. However, $w = 20$ is chosen for all predictors, as it produces lower prediction error and requires less computation process, memory storage, and energy usage compared to $W = \{5, 10\}$. To avoid energy or time wastage, $w = 20$ is chosen, since the prediction error of $w = 20$ has an insignificant difference of 0.25 compared to $w = 30$. For instance, if traffic congestion only lasted for 15 minutes, only 5 minutes of energy wasted for $w = 20$, rather than 15 minutes of energy consumption wasted for $w = 30$, due to 100% switched on of streetlight when road traffic congestion is detected. If an accident happens, but $w = 30$ indicates low traffic period, then $w = 30$ needs to wait 30 minutes later for the next prediction cycle, which is a waste of time as compared to $w = 20$. A higher prediction frequency can produce more accurate results (Kourentzes & Crone, 2008), where $w = 20$ predicts more frequently than $w = 30$ that is two and three times per hour respectively, thus allowing $w = 20$ to cover wider range of road traffic scenarios.

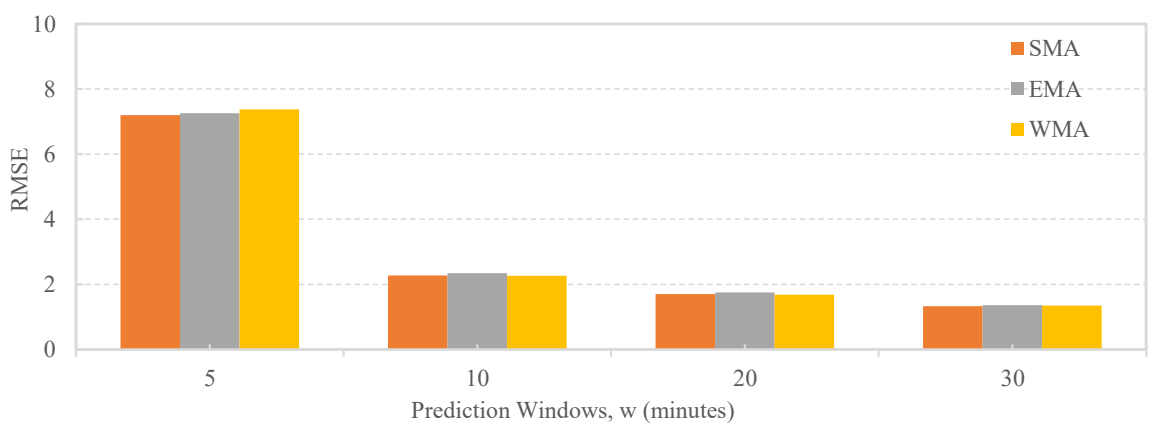


Figure 3.5: The RMSE of considered prediction models (average) at different w values for 10 different simulation scenarios of TALiSMaN at linear topology.

3.6.4 Determination of Previous n Weeks

The simulation is run for 10 iteration sets with predictors estimating every $w = 20$ minutes for this simulation to discover the total previous n weeks data that is required to produce the least prediction error result. The n value ranging from 2 to 10 days for SMA, EMA and WMA predictors are assessed.

Figure 3.6 highlights that the selected predictors can produce their best performance at $n = 10$ as it shows the least RMSE values among 2 to 10 days. Although the predictors produce the least prediction errors at $n = 10$ but the RMSE values are insignificant compared to the values for SMA, EMA and WMA at $n = 7$, which is 14%, 24% and 6% difference, respectively. The memory storage for a day of traffic data requires 3 KB, 10 days of week will require 210 KB while 7 days requires 147 KB, which is 43% lesser. Since WSN provides limited memory storage, hence selecting based on memory requirement outweighs the prediction accuracy. Thus, $n = 7$ days of week is chosen for the simulation and evaluation of the predictors as it requires less memory to store; and less processing power to compute a total of 7 weeks data compared to 10 weeks traffic data.

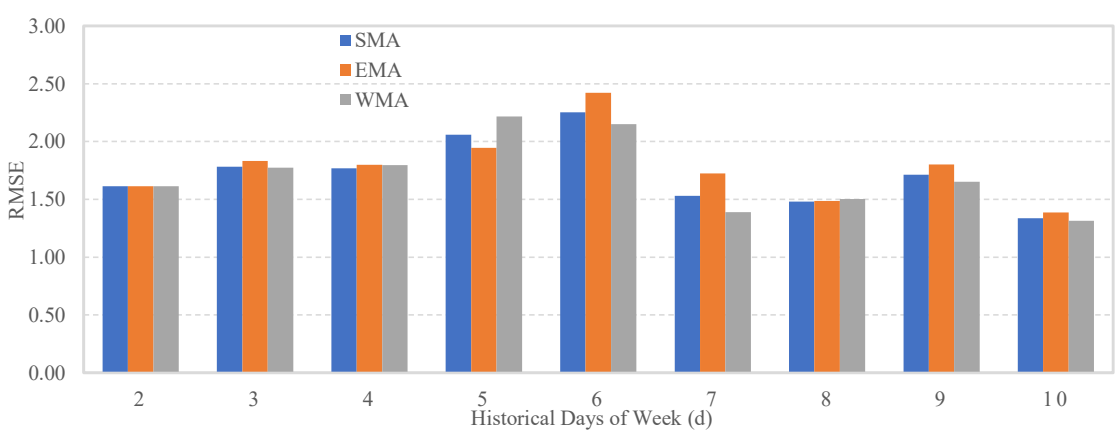


Figure 3.6: The minimum RMSE values for three considered predictors with $w = 20$ at various n days used for traffic prediction.

3.6.5 Prediction Technique Selection

Predictor selection is the process to discover the most ideal predictor for TALiSMaN with predictive control, which is typically by evaluating its prediction error. As mentioned in Section 3.6, RMSE is used to evaluate the accuracy of the estimated value produced by the predictors against the observed value generated by StreetlightSim. However, it is inapt to depend on a factor alone for predictor selection, as computation overhead (Indu, 2014) may affect the overall prediction performance due to the restriction of TALiSMaN. Due to the resource restriction, for instance, processing power and memory constraint in WSN (Huan & Kim, 2020), the process to select a predictor needs to consider both computing resources and prediction accuracy.

Based on the prediction parameters obtained in Section 3.6, SMA, EMA and WMA predictors required a significant amount of memory to estimate $\acute{\varepsilon}_d$, where $n = 7$ and $w = 20$ minutes are chosen for all three predictors. Given that all three predictors have the same prediction parameters, their memory requirement will be the same, hence, memory requirement is unjustifiable for predictor selection.

In terms of processing power, since each instruction executes one arithmetic operation and sensor node processing power is limited to eight million instructions per second (MIPS), achieving the desired values for all three predictors will take less than one second. As a result, the computational cost of estimating road traffic for candidate predictors is negligible.

Based on the C code from Table 3.1, the number of arithmetic operations for SMA is $(n - 1) + 1 = n$, where n is number of the x terms and 1 represent the $/n$. For EMA and WMA, both have their respective weighing factor. The number of steps of weighing factor

of EMA alone already equal to whole operation of SMA, number of steps of WMA weighing factor is even more than that. Hence, in the case number of arithmetic operations, the simple moving average shows obvious advantage compared to other two, which require more arithmetic operations than SMA.

Although all predictors have similar RMSE value as shown in Table 3.2, SMA is less complex among the three predictors, due to the absence of weighing factor. The SMA is clearly a feasible choice for TALiSMaN with predictive control.

Table 3.1: The algebraic expression and programming code for SMA, EMA and WMA predictors to estimate road traffic

Predictor	Algebraic expression	C code
SMA	$\acute{\varepsilon}(t) = \frac{\sum_{d=1}^{n} \varepsilon_d}{n}$	int $x_1, x_2, \cdots, x_n, n$; double y; $y = (x_1 + x_2 + \cdots + x_n) / n$
EMA	$\acute{\varepsilon}(t) = a * \varepsilon_{d-1} + (1 - a) * \acute{\varepsilon}_{d-1}$	int x_{n-1}, x_n, y_{n-1}, n; double a, y; $a = 2 / (1 + n)$ $if\ (n == 2)\ y = (x_1 + x_2) / 2$ $y = (a * x_{n-1}) + ((1 - a) * y_{n-1})$
WMA	$\acute{\varepsilon}(t) = \frac{\sum_{d=1}^{n}(n - d + 1)\, \varepsilon_d}{a}$	int $x_1, x_2, \cdots, x_n, n$; double a, y; $a = n * (n + 1) / n$ $y = (x_1 * n + x_2 * (n - 1) + \cdots + x_n * 1) / a$

Table 3.2: The RMSE, weighing factor, complexity required for SMA, EMA and WMA predictors to produce an accurate road traffic

Predictor	RMSE	Weighing factor	C code Complexity
SMA	1.613	no	Simple
EMA	1.640	yes	Complex
WMA	1.611	yes	Complex

3.7 Summary

This chapter proposed TALiSMaN with predictive control, a networked street lighting scheme utilise prediction model to ease network congestion. The proposed scheme integrates TALiSMaN, a lighting scheme that achieves efficient energy consumption and usefulness of street lighting by dynamically adjusts the lighting condition while it detects road traffic. There are underlying issues of TALiSMaN, namely network congestion and packet drop issues during road traffic peak period. The issue leads to interruption of the operation of TALiSMaN as streetlights are unable to turn on or off accordingly and such interruption can degrade its usefulness. This is where predictive control came in, to overcome these limitations by forecast the traffic condition, then manage data broadcasting, and deliver a consistent streetlight usefulness throughout the night. To identify a suitable road traffic predictor for this predictive control enhancement, the candidate real-time online predictors, that is SMA, EMA and WMA was evaluated based on prediction parameters, RMSE and number of operations steps. SMA proved to be the most feasible road traffic predictor for TALiSMaN with predictive control as it has the lowest mathematical operation while maintaining a close range RMSE as other predictors. The prediction parameters that produced the least prediction errors when the data is aggregated with days of the week strategy, include $w = 20$ minutes and $n = 7$ days of historical data. The road traffic

congestion threshold value, φ is obtained by the averaging the total road traffic data from previous week of the same d day, to be compared with the predicted data for road traffic congestion detection. If road traffic peak period is detected, then the proposed scheme will stop data broadcasting and turn on all streetlights for 20 minutes. The proposed scheme will proceed the operation as intended by TALiSMaN scheme when no congestion detected. In the next chapter, TALiSMaN with predictive control and the selected prediction parameters will be evaluated in two different case scenarios using two different road traffic volume.

CHAPTER 4

SIMULATION AND ANALYSIS OF TALISMAN WITH PREDICTIVE CONTROL

4.1 Introduction

This chapter includes an overview of the assumptions made for this simulation, followed by the simulation tools and configuration setup applied in the simulation. Besides, this chapter also reviews the performance evaluation of TALiSMaN with predictive control in different network topologies setup. Then followed by the performance metrics namely PDR, TEC, and total utility, which are used to test a range of number of nodes on TALiSMaN with and without predictive control.

4.2 Assumptions

The assumptions made for this simulation are as the following:

i. Streetlights operation hour is from 16:00 until the next day 08:00, to represent the street lighting operational hours in extreme scenarios.

ii. Streetlights operate throughout 16-hour with a 25 W LED lamp (Panasonic Life Solutions India Pvt. Ltd., 2020) using TALiSMaN lighting scheme.

iii. The network topology is based on the street lighting distribution for residential area. Reason for that is because road traffic does not occupy the residential street throughout every hour and operating for 16 hours causes high energy consumption. Hence, adopting the adaptive networked street lighting system on residential area allows streetlight to operate when required.

iv. The sensor node attached streetlights are positioned in the middle of the road with an average distance of 30 m between each streetlight (Lau et al., 2013), to ensure full lighting coverage for the distance between two streetlights. The streetlights are turned on to 100% brightness when the motorist is detected.

v. The road traffic profile for each day of the week is the average traffic collected over a year time interval in UK, where weekdays are considered as workdays and school days as previously described in Section 3.6.2. The road traffic users will be added randomly into the simulation at any point of the road and anytime based on the traffic pattern predefined in the road traffic distribution profile obtained from Southampton City Council (European Platform on Mobility Management, n.d.). The road traffic profile does not consider the event of accident, as the occurrence of the accident is very random and hard to simulate for this study.

4.3 Simulation Setup

The proposed scheme is implemented in StreetlightSim. StreetlightSim is an open-source simulation environment that is used to implement TALiSMaN (Lau et al., 2014). The simulation environment utilised both OMNeT++ and SUMO tools, to represent all the performance and operation of streetlights, such as traffic detection, traffic pattern generation, and evaluation of the practicality of the TALiSMaN through the perspective of road traffic. The following parameters were used:

i. The simulation is run for 10 repetition sets, as shown in Section 3.6.1, it is adequate to produce accurate results without producing unnecessary simulation iteration.

ii. As presented in Section 3.6.3, the prediction window, $w = 20$ minutes, with $\vartheta = 72$ timeslots are chosen, as it is sufficient to produce negligible traffic prediction error throughout the street lighting operating hours for a day.

iii. The prediction length, n is set to 7 days of week for the SMA predictor, as it is ample to predict road traffic volume and requires less memory storage, as demonstrated in Section 3.6.4.

iv. The total 10 weeks of road traffic historical data is initially collected before prediction starts.

v. The linear and cross-junction network topologies are considered, each with 12 streetlights shown in Figure 4.1, and 19 streetlights shown in Figure 4.6 assign across the road segments, respectively.

vi. The total road traffic volume of 438 and 3508 vehicles per day (Lau et al., 2014) are applied, as these figures represent the first and third quartile for the traffic volume collected at residential roads over a year based on Southampton City Council (European Platform on Mobility Management, n.d.), respectively.

4.4 Evaluation Parameters

In this study, the performance of proposed solution is evaluated in terms of Packet Dropped Ratios (PDR), usefulness and Total energy consumption (TEC) to demonstrate the effectiveness of real-time short-term traffic prediction in TALiSMaN.

PDR is chosen as the parameter as it presents the number of packets that are dropped during data transmission process among streetlights. Furthermore, PDR can be used to

identify problems that might lead to poor throughput or poor load distribution. The equation of PDR is given by Equation 4.1:

$$PDR = \frac{P_d}{P_s} \times 100\% \qquad \text{Equation 4.1}$$

Where:

P_d = The number of packets dropped.

P_s = The total number of packets sent in the network.

The usefulness of streetlight towards road traffic is obtained using the streetlight utility model in StreetlightSim (Lau et al., 2014). The usefulness model can be used as a parameter to determine the correctness, competence, and impact of the proposed scheme towards existing scheme.

TEC refers to the total energy consumed by a streetlight per hour, which is calculated by the energy model in StreetlightSim (Lau et al., 2014). Efficient energy consumption is main attraction of TALiSMaN when powered with electrical grid. However, in considering rural area, energy constraint is one of the factors affecting the performance of TALiSMaN when implement with the off-grid power supply, also known as TALiSMaN-Green. Since the battery used in off-grid scheme is very bulky and heavy to carry around, it is not feasible to constantly replace the batteries once it fails. It is crucial to extend the network lifetime as to ensure TALiSMaN scheme can perform effectively, with or without power-grid supply.

4.5 Case study A: Linear Network Topology

To achieve a performance review of TALiSMaN with predictive control on linear network topology in this case study, the road traffic volume, 438 and 3508 vehicles per day is applied. The simulation of TALiSMaN with predictive control is simulated in StreetlightSim based on the parameters defined in Section 4.2 and Section 4.3. The linear network topology simulated into StreetlightSim represents the distribution of 12 streetlights across a 300 m distance straight road segment, as illustrated in Figure 4.1. Thus, in this case study, the predictive control system of the streetlights is built to predict road traffic and control data broadcasting based on traffic condition, while streetlights operate as required throughout 16-hour of TALiSMaN lighting operation with a 25 W LED lamp. This case scenario aims to evaluate the performance of TALiSMaN scheme and TALiSMaN with a predictive control scheme in terms of PDR, usefulness, and TEC.

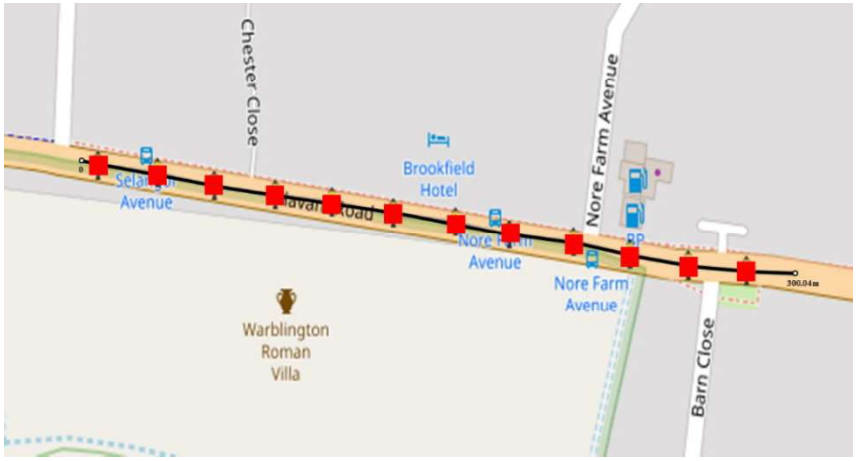
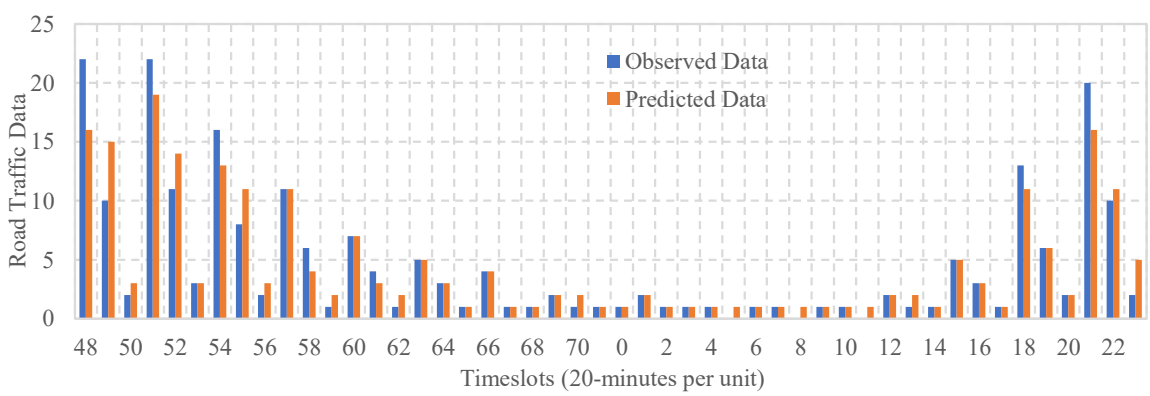


Figure 4.1: The straight road segment with distance of approximately 300 m is simulated in StreetlightSim as linear network topology associated with 12 red dots to represent the streetlights (the map was modified from JOSM).

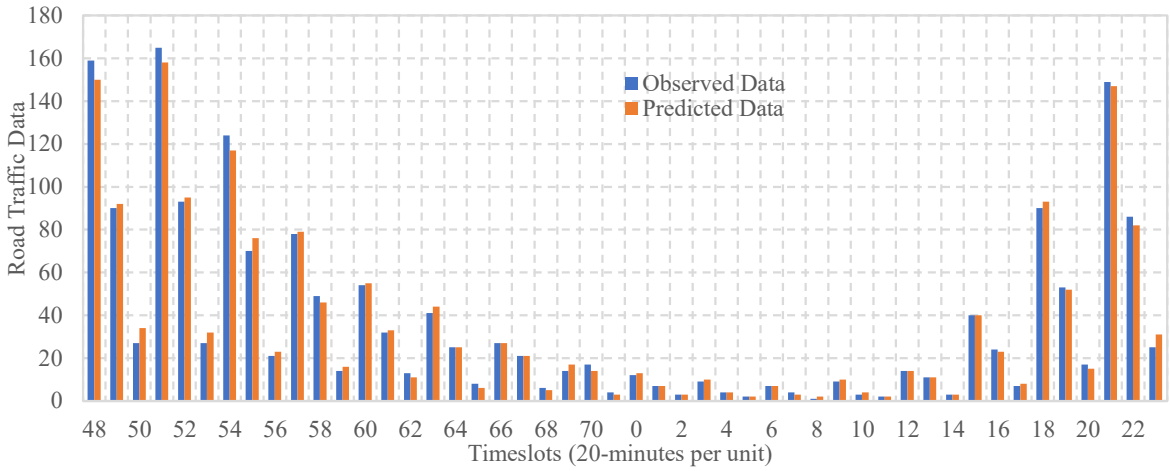
4.5.1 Prediction Accuracy

This section analyses the Prediction Accuracy (PA) of the average road traffic data predicted by TALiSMaN with predictive control against the average observed road traffic data generated by TALiSMaN throughout streetlight operation hour when applied with (a) 438 and (b) 3508 road traffic per day under linear topology. The streetlight operation hour is divided into equal-sized ϑ with $w = 20$ minutes interval as defined in Section 4.3, where $\vartheta = 48$ represents 16:00-16:20, $\vartheta = 49$ is 16:20-16:40 and so forth. Both predicted data of 438 and 3508 traffic flow has almost similar trend of accuracy with the observed data.

The result of predicted road traffic data is closely comparable with the observed road traffic data, where the maximum difference for Figure 4.2 (a) five, and (b) nine road traffic data. At certain hour, both Figure 4.2 (a) and (b) show the least difference between the observed and predicted road traffic data is zero. Although the differences of road traffic data for Figure 4.2 (b) is more than (a), the differences are insignificant when compared to the road traffic volume flow for each respective ϑ. For example, the observed and predicted road traffic data at $\vartheta = 48$ are (a) 22 and 16, and (b) 159 and 150, then the differences are 6 and 9 road traffic data. Thus, the adopted model can accurately predict the road data.



(a) 438 throughout streetlight operation timeslot



(b) 3508 throughout streetlight operation timeslot

Figure 4.2: Simulation reults show the road traffic data for each ϑ when operating with TALiSMaN and TALiSMaN with predictive control schemes under linear network topology at different road traffic volume of (a) 438 and (b) 3508 vehicles per day.

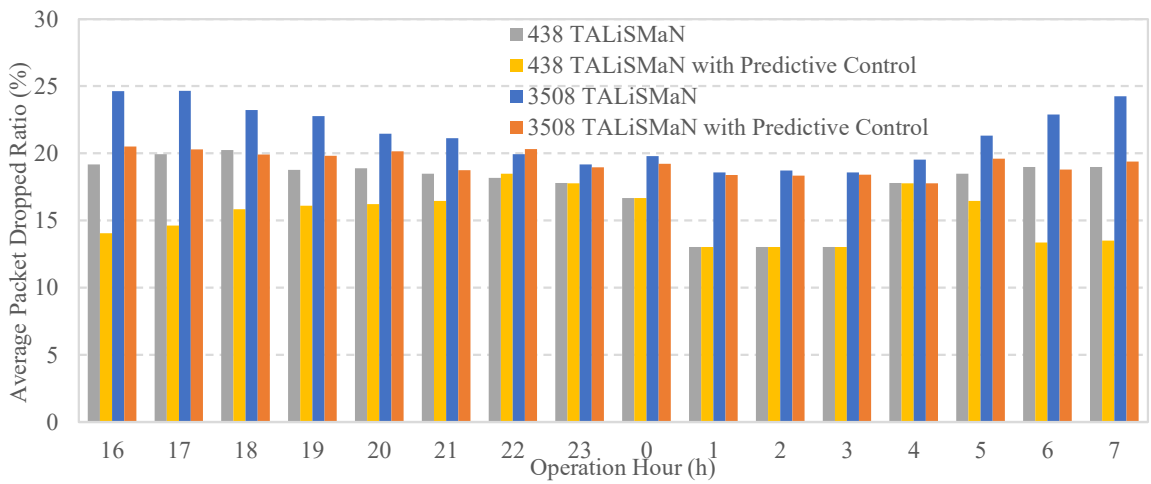
4.5.2 Packet Dropped Ratio

Figure 4.3 illustrates the PDR for TALiSMaN and TALiSMaN with predictive control schemes at different streetlight operational hour and ϑ during road traffic volumes 438 and 3508 vehicles per day. Figures are separated into streetlight operational hour and ϑ because TALiSMaN is simulated based on operational hours, but prediction is performed every $w = 20$ minutes interval ϑ as defined in Section 4.3, where PDR against ϑ can provide further insight on the performance of TALiSMaN with predictive control.

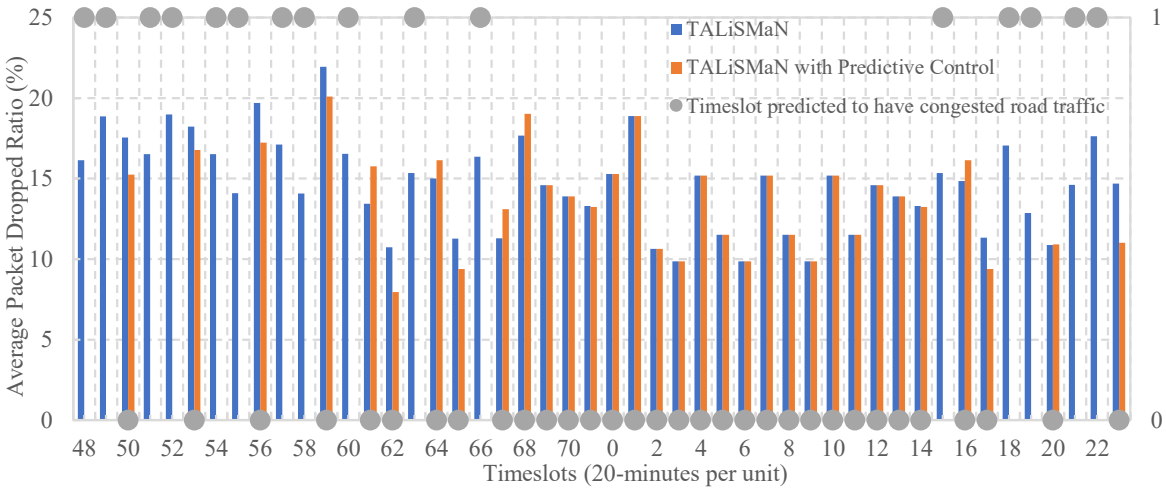
As shown in Figure 4.3 (a) TALiSMaN with predictive control scheme experiences lower average PDR for streetlight operation hour 16:00 to 21:00 and 04:00 to 07:00 compared to TALiSMaN. This is because road traffic condition is predicted to be congested at the ϑ in these operation hours, as indicated by grey dots in Figure 4.3 (b) and (c), i.e., $\vartheta = \{48, 49, 51, 52, 54, 55, 57, 58, 60, 63, 66, 15, 18, 19, 21, 22\}$. Both schemes receive similar PDR results during operation hour 22:00 to 03:00. These results are expected as streetlight

operation fall back normal TALiSMaN when non-congested road traffic is predicted (see Section 3.5).

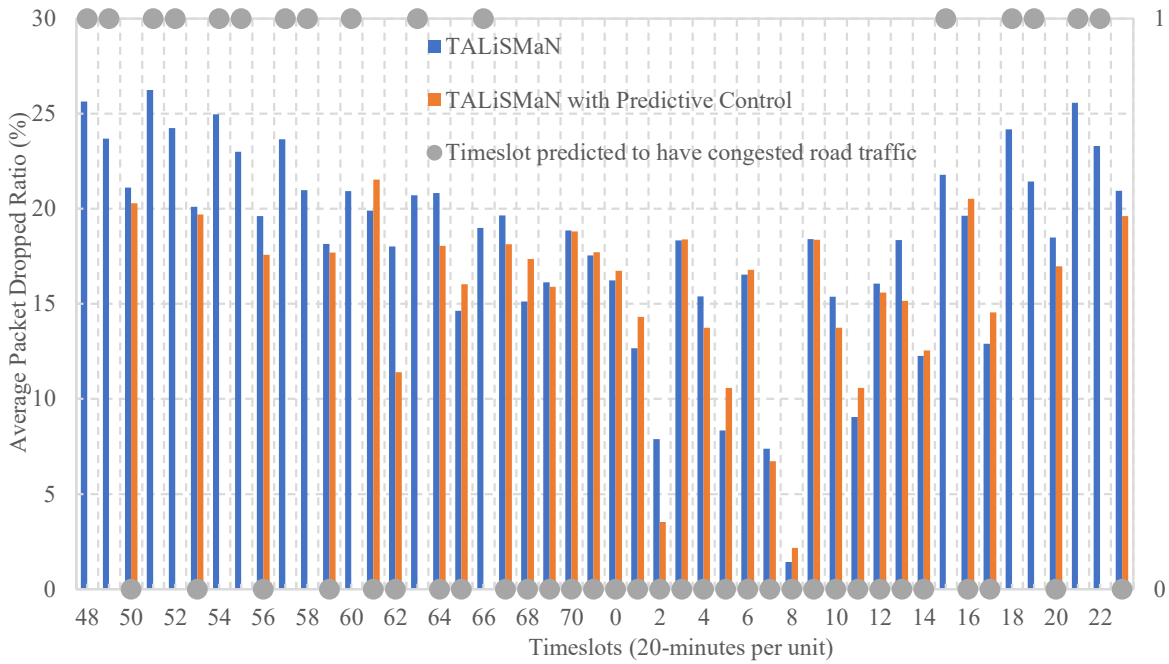
Although TALiSMaN with predictive control scheme has reduced PDR by 0.01% – 5.6% on average per day as illustrated in Figure 4.3 (a), PDR shows significant reduction of 12.9% - 26.2% for ϑ that is predicted to have congested road traffic, as shown in Figure 4.3 (b) and (c). Hence, it can be explained that TALiSMaN with predictive control will perform better as it can lower PDR in the presence of heavy flow of road traffic.



(a) 438 and 3508 road traffic per day throughout streetlight operation hour



(b) 438 throughout various timeslots, ϑ



(c) 3508 throughout various timeslots, ϑ

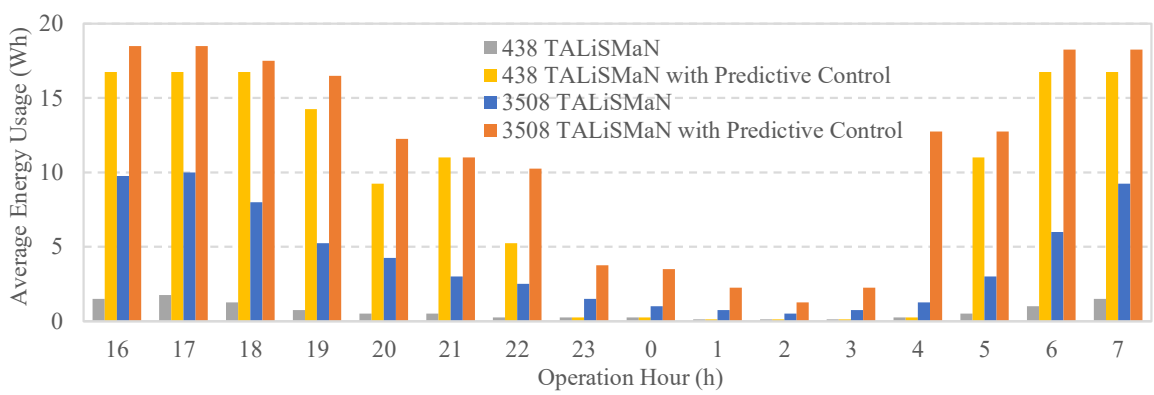
Figure 4.3: Simulation results showing the average PDR when operating TALiSMaN and TALiSMaN with predictive control schemes using linear network topology at different road traffic volume of (a) 438 and 3508 road traffic per day, operate througout streetlight operation; while (b) 438 and (c) 3508 are throughout the 20-minutes interval ϑ. The timeslots that are predicted to have congested road traffic are indicated with grey dots.

4.5.3 Energy Usage of the Streetlights

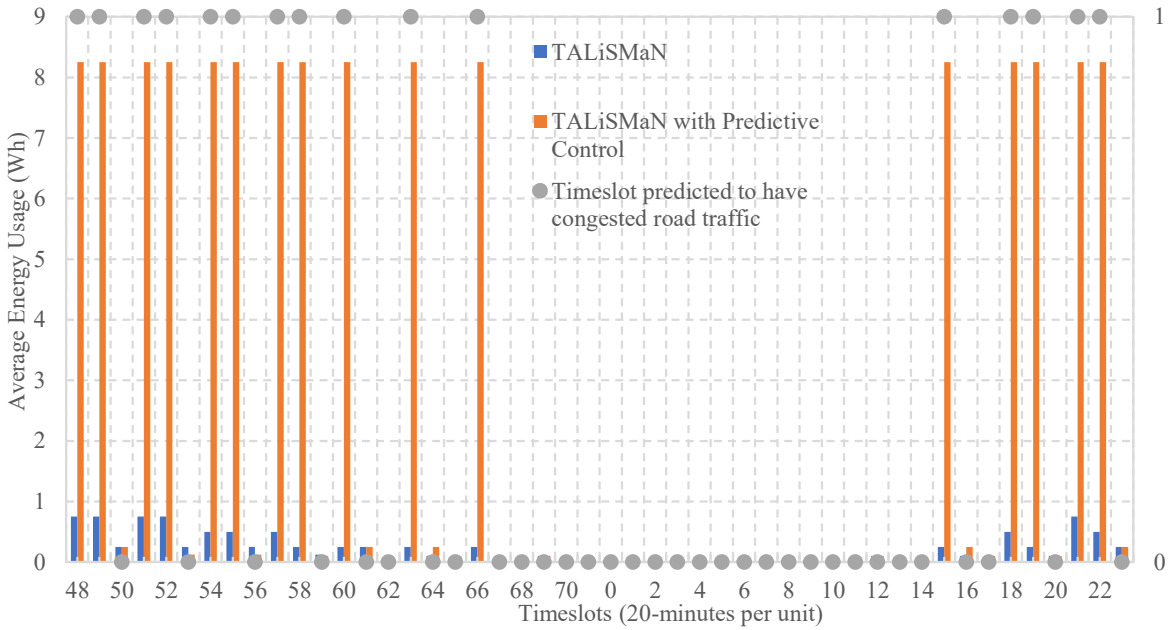
This section reviews the effect of road traffic volume per day towards the TEC for TALiSMaN and TALiSMaN with predictive control schemes under linear network topology. Figure 4.4 (a) shows TEC per hour throughout streetlight operation hour whereas Figure 4.4 (b) and (c) show TEC in each interval ϑ. Based on the results, an increase in road traffic volumes lead to the increment of streetlight TEC. As shown in Figure 4.4 (a), TALiSMaN has the difference of 0.38 – 8.25 Wh in terms of energy usage while TALiSMaN with predictive control has a difference of 0 – 12.5 Wh for 3508 road traffic per day compared to 438 road traffic per day.

Figure 4.4 (a) indicates that the streetlights consume more energy for TALiSMaN with predictive control scheme at operation hour 16:00 to 21:00 and 03:00 to 07:00, compared to TALiSMaN. The increment of energy usage for 438 road traffic per day is 5 – 15.75 Wh, while 3508 road traffic per day is 0.75 – 12.25 Wh. The occurrence of road traffic congestion at certain ϑ (from $\vartheta = 48$ to $\vartheta = 66$ and $\vartheta = 15$ to $\vartheta = 21$) causes the increase in frequency and length of streetlights turn on in full brightness period, which increase the energy consumed per hour.

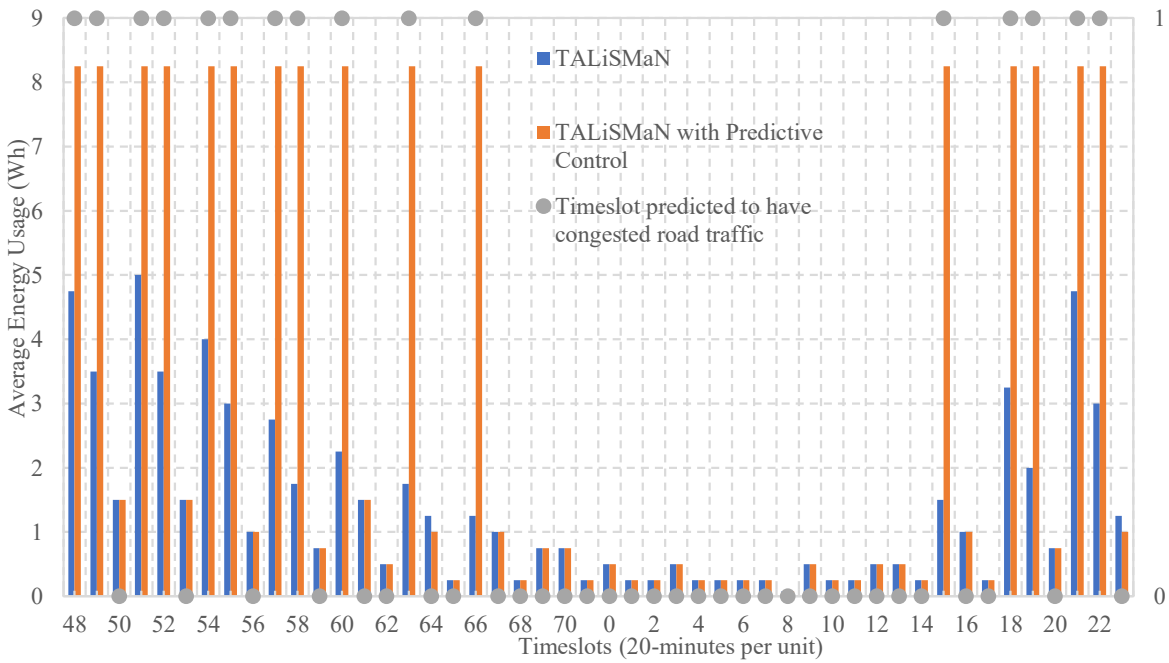
For example, when road traffic condition is predicted to be congested, as indicated by grey dots at $\vartheta = \{48, 49, 51, 52, 54, 55, 57, 58, 60, 63, 66, 15, 18, 19, 21, 22\}$, the streetlight operating TALiSMaN with predictive control scheme is fully turn on and last for 20 minutes at each ϑ (when $w = 20$ minutes is applied). This has caused an increment of 3.3 – 8.0 Wh for ϑ predicted to be congested as shown in Figure 4.4 (b) and (c). (Note that, $\vartheta = \{48, 49\}$ represents streetlight operation hour 16:00 to 16:20 and 16:20 to 16:40, respectively). However, the energy consumed by TALiSMaN with predictive scheme remains the same as TALiSMaN scheme at $\vartheta = 50$ where streetlight resumes normal TALiSMaN operation when non-congested road traffic is predicted.



(a) 438 and 3508 road traffic per day throughout streetlight operation hour



(b) 438 throughout various timeslots, ϑ



(c) 3508 throughout various timeslots, ϑ

Figure 4.4: Simulation reults showing the mean TEC of the streetlights while operating TALiSMaN and TALiSMaN with predictive control schemes using linear network topology at different road traffic volume of (a) 438 and 3508 road traffic per day throughout streetlight operation hour; whist (b) 438 and (c) 3508 are for the 20-minutes interval ϑ. The timeslots that are predicted to have congested road traffic are indicated with grey dots.

4.5.4 Usefulness of the Streetlights

The usefulness of streetlights to road traffic, while streetlights operate with TALiSMaN and TALiSMaN with predictive control schemes, are assessed by the streetlight usefulness model that is available in StreetlightSim (Lau et al., 2014). The usefulness model measures the illumination of streetlight experience by the simulated road users, to ensure the proposed scheme fulfils the lighting condition required by the road users. The scheme would be impracticable if the streetlight operating under the proposed lighting scheme is not useful to road users, even though the scheme is extremely energy efficient and delivers a low packet drop ratio. Thus, this subsection analyses the effect of road traffic volumes on the streetlight usefulness when operates with different lighting schemes.

Figure 4.5 highlights that the usefulness of TALiSMaN with predictive control significantly improves during heavy road traffic scenarios, i.e., at operation hour 16:00 to 22:00 and 05:00 to 07:00, when compared to TALiSMaN. For 438 road traffic per day, the average improvement in streetlight usefulness is 0.1% – 0.4%, with a range of 94.6% – 98.1%, whereas for 3508 road traffic per day, the average increase is 0.1% – 2.9%, with a range of 95% – 98%. The usefulness of the streetlights remains the same road during light traffic scenarios, i.e., at operation hour 23:00 to 04:00, as shown in Figure 4.5. The reason for this is that when light road traffic scenario is predicted, the operation reverts to normal TALiSMaN, as described in Section 3.5. All these results indicate that the implementation of TALiSMaN with predictive control in a linear streetlight network topology has improved, the usefulness during heavy road traffic scenarios, which is as intended for this study.

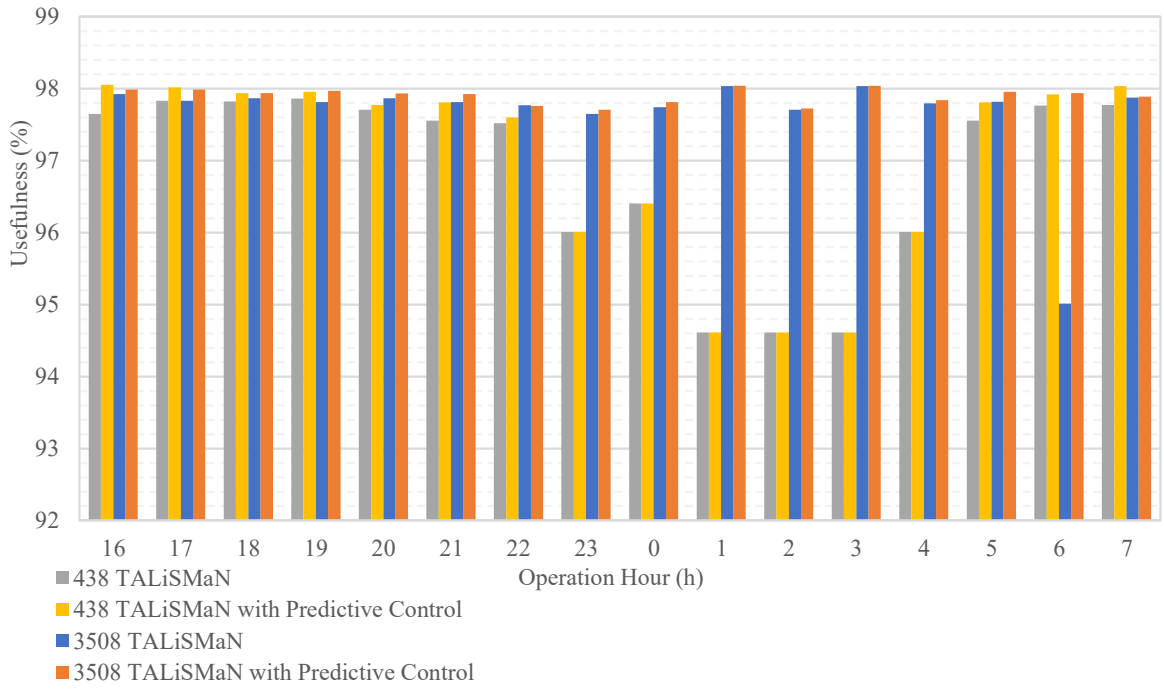


Figure 4.5: Simulation reults showing the average usefulness of the streetlights received by the simulated motorists under TALiSMaN and TALiSMaN with predictive control schemes in 438 and 3508 road traffic volume per day for linear network topology

4.6 Case Study B: Cross-Junction Network Topology

Ideally, a lightning scheme should be designed to be functional regardless of the road topology, hence it is better if TALiSMaN with predictive control scheme undergoes further testing on different road topology. In this case, the cross-junction topology is simulated to compare the performance of TALiSMaN with predictive control scheme within a higher density of streetlights. The cross-junction topology is comparatively similar to linear topology, as the cross-junction topology represents two linear topologies cross over at an intersection point, where streetlights density is higher. Since sensor nodes are attached on streetlights, the increase in density of sensor nodes can cause network overload for TALiSMaN scheme, due to communication bandwidth is scare and share among neighbouring nodes within 100 m from the intersection point.

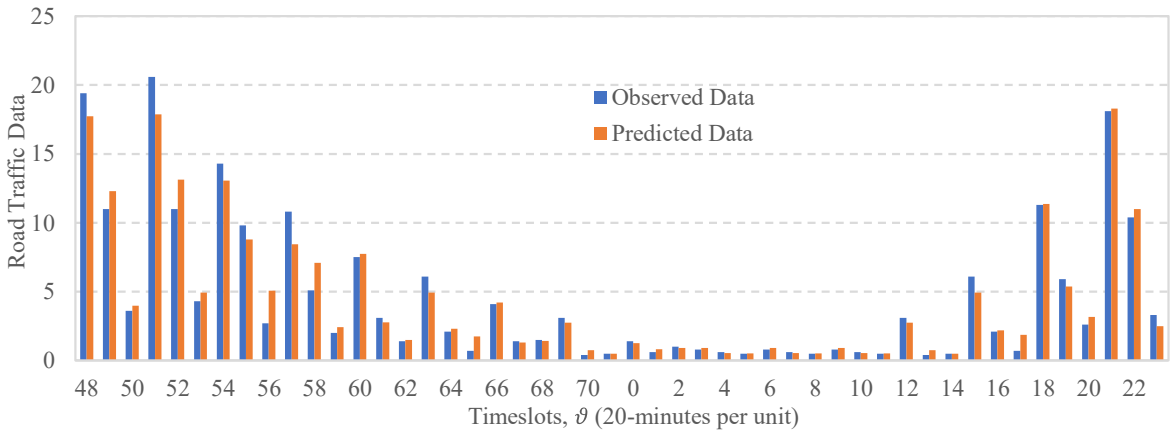
Figure 4.6 shows the illustration of a typical cross junction road topology that is simulated into StreetlightSim, which represents the distribution of 19 streetlights across a 492 m distance straight road segment. It can be observed that the density of the streetlight at the intersection is higher, its effects on TALiSMaN will be evaluated. The simulation parameters are those that are defined in Section 4.2 and Section 4.3.

Figure 4.6: The cross-junction road segment with distance of approximately 492 m is simulated in StreetlightSim as cross-junction network topology associated with 19 red dots to represent the streetlights across the residential area (the map was modified from Google Maps).

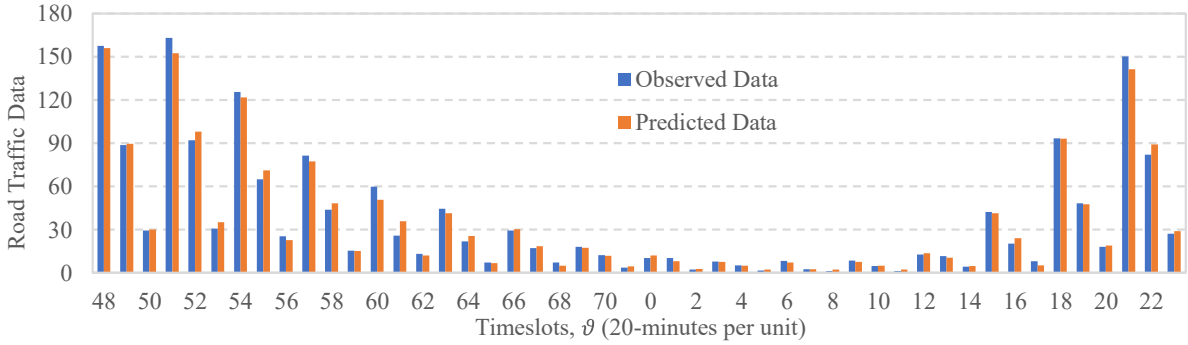
4.6.1 Prediction Accuracy

This section analyses the accuracy of the average road traffic data predicted by TALiSMaN with predictive control against the average observed road traffic data simulated by TALiSMaN within the streetlight operation hour when applied with Figure 4.7 (a) 438 and (b) 3508 road traffic per day under cross-junction road topology.

The result of predicted road traffic data is closely comparable with the observed road traffic data, where the maximum difference for Figure 4.7 (a) three, and (b) ten road traffic data. At certain hour, both Figure 4.7 (a) and (b) show the least difference between the observed and predicted road traffic data is zero. Although the differences of road traffic data for Figure 4.7 (b) is more than (a), the differences are insignificant when compared to the road traffic volume flow for each respective ϑ. For example, the observed and predicted road traffic data at $\vartheta = 48$ are (a) 19 and 18, and (b) 158 and 156, where the differences are 1 and 2 road traffic data. Thus, the adopted model can accurately predict the road data.



(a) 438 throughout streetlight operation timeslot, ϑ



(b) 3508 throughout streetlight operation timeslot, ϑ

Figure 4.7: Simulation reults show the road traffic data for each ϑ when operating with TALiSMaN and TALiSMaN with predictive control schemes under cross junction topology at different road traffic volume of (a) 438 and (c) 3508 road traffic per day.

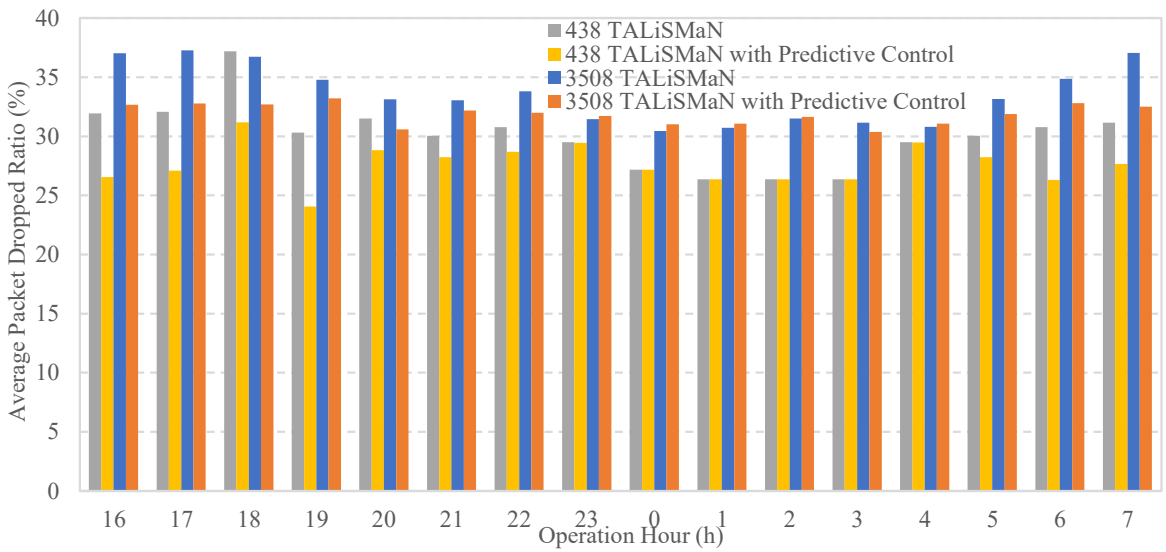
4.6.2 Packet Dropped Ratio

Figure 4.8 shows the results of PDR for TALiSMaN and TALiSMaN with predictive control schemes on different road traffic volumes (438 and 3508 road traffic per day) throughout streetlight operation hours and different ϑ using the cross-junction network topology. The results show more details on the performance TALiSMaN with predictive scheme by analysing each ϑ interval during streetlight operation hour.

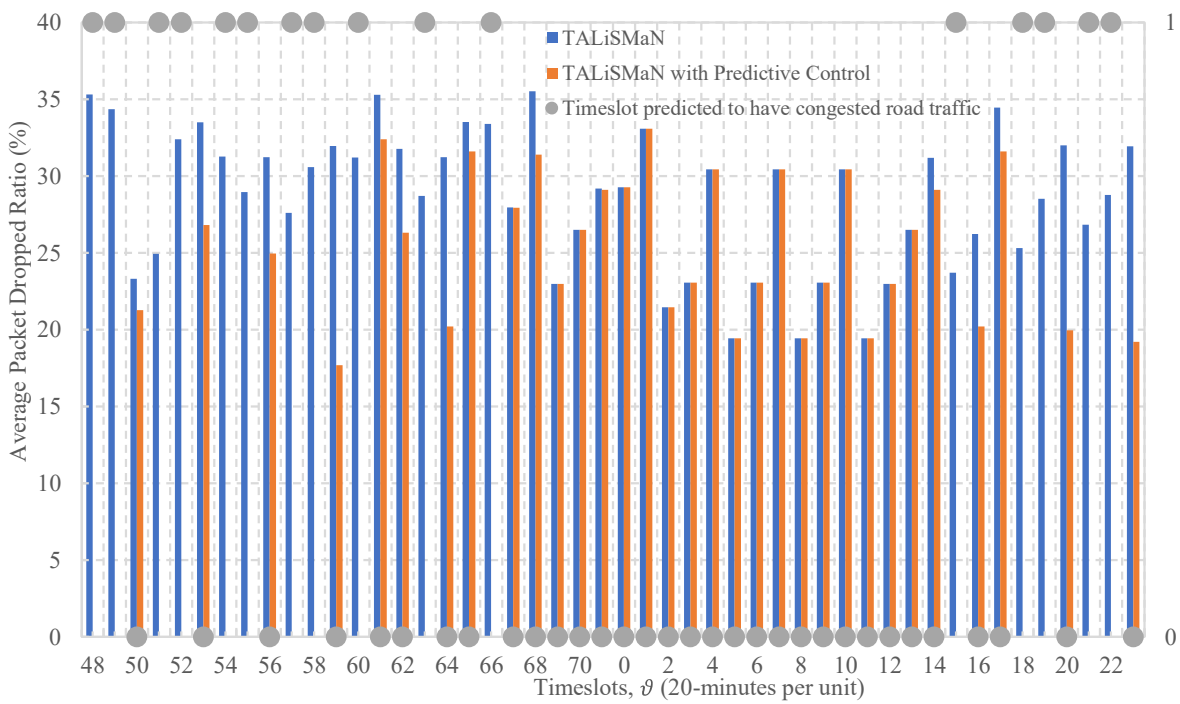
As shown in Figure 4.8 (a), TALiSMaN with predictive control scheme experiences lower average PDR for streetlight operation hour 16:00 to 22:00 and 05:00 to 07:00 compared to TALiSMaN. This is because road traffic condition is predicted to be congested at the ϑ in these operation hours, as indicated by grey dots in Figure 4.3 (b) and (c), i.e., $\vartheta = \{48, 49, 51, 52, 54, 55, 57, 58, 60, 63, 66, 15, 18, 19, 21, 22\}$. When road traffic congestion is predicted, the proposed scheme stops broadcast of data packet, as mentioned in Section 3.5. Thus, TALiSMaN with predictive control scheme has significantly reduced PDR by 23.7% – 37.4% for ϑ that were predicted to have congested road traffic as shown in Figure 4.8 (b) and (c), despite the PDR reduction of 0.04% – 6.28% on average per day, as illustrated in Figure 4.8 (a). Both schemes receive similar PDR results during operation hour 23:00 to 04:00. These results are expected as streetlight operation fall back normal TALiSMaN when non-congested road traffic is predicted.

To compare with Case study A: Linear Network Topology in Section 4.5, both network topologies show that the road traffic volume increases along with the average PDR. However, the cross-junction network topology encounters higher average PDR for both TALiSMaN with and without predictive control schemes, with the range of 23.7% to 37.4% as opposed to linear network ranging from 12.9% to 26.2%. Reason for that is because the

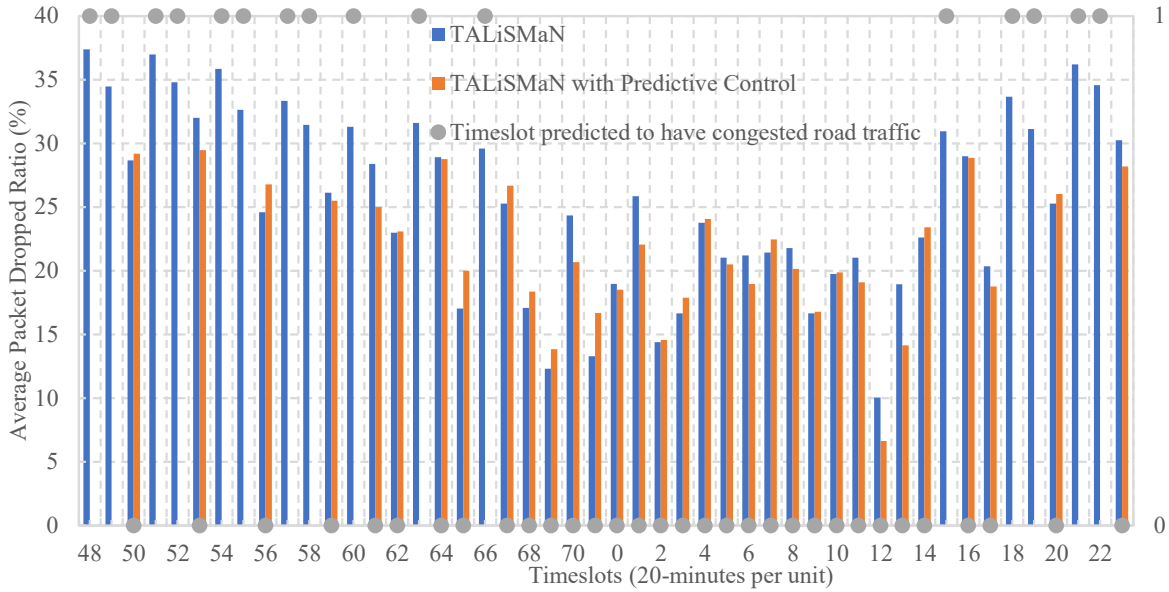
density of sensor nodes at the intersection point tends to overload the network with the limited network buffer capacity (Benmansour et al., 2020), causing the increment of PDR during data transmission especially in heavy road traffic condition.



(a) 438 and 3508 throughout streetlight operation hour



(b) 438 throughout various timeslots, ϑ



(c) 3508 throughout various timeslots, ϑ

Figure 4.8: Simulation reults showing the average PDR when operating TALiSMaN and TALiSMaN with predictive control schemes under cross-junction network topology at different road traffic volume of (a) 438 and 3508 road traffic per day througout streetlight operation; while (b) 438 and (c) 3508 are thtoughout the 20-minutes ϑ interval. The timeslots that are predicted to have congested road traffic are indicated with grey dots.

4.6.3 Energy Consumption of the Streetlights

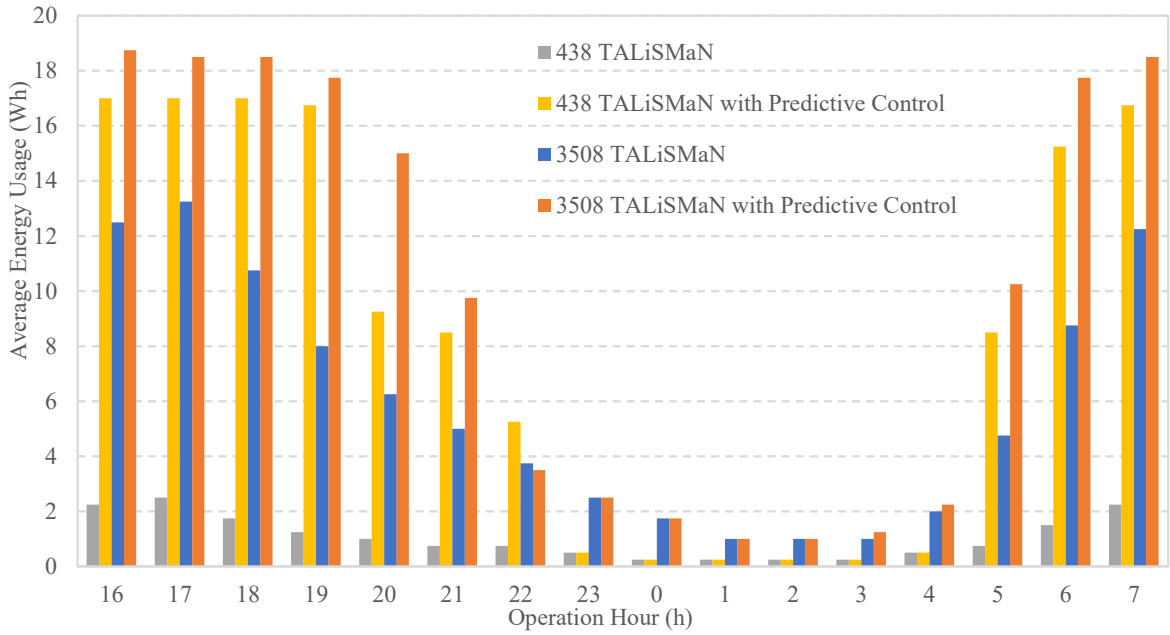
This section reviews the effect of different road traffic volume per day towards the TEC for TALiSMaN and TALiSMaN with predictive control schemes under cross-junction network topology. Figure 4.9 (a) show TEC throughout streetlight operation hour, while Figure 4.9 (b) and (c) show TEC throughout 20 minutes interval ϑ.

TALiSMaN with predictive control scheme consumes more energy than TALiSMaN scheme during predicted road traffic congestion hour from 16:00 to 22:00 and 05:00 to 07:00, as shown in Figure 4.9 (a). For 438 road traffic per day, TALiSMaN with predictive control scheme consumes 4.5 – 15.75 Wh more energy than TALiSMaN, whereas 0.25 – 9.75 Wh for 3508 road traffic per day.

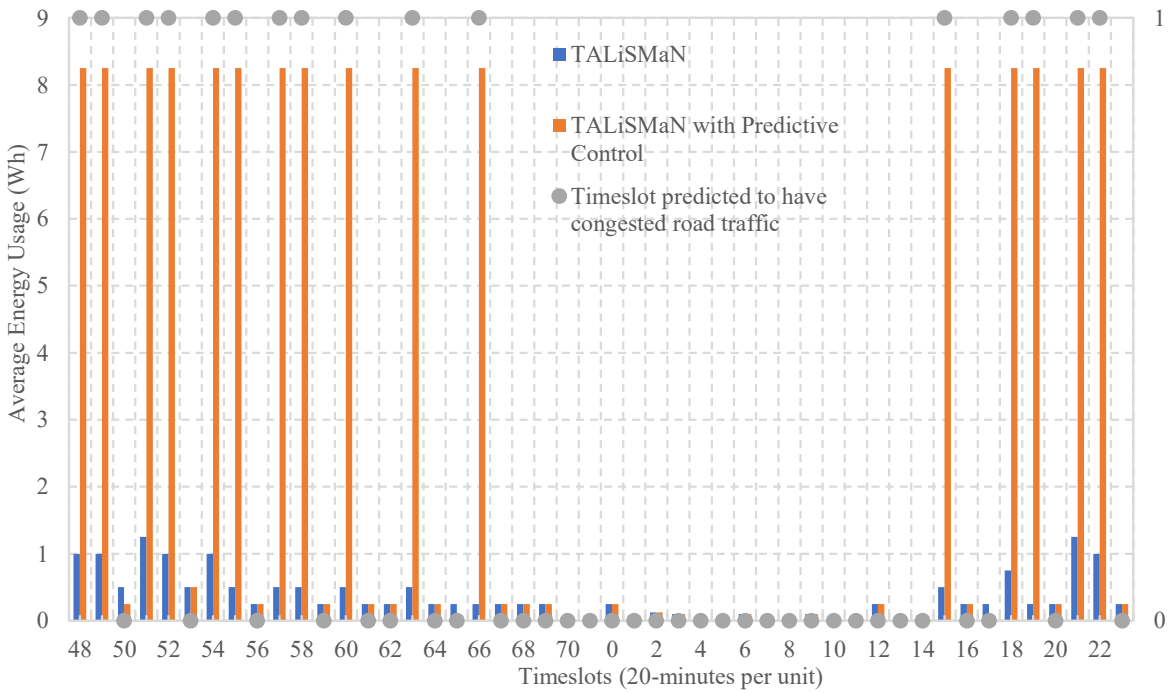
The occurrence of road traffic congestion at $\vartheta = \{48, 49, 51, 52, 54, 55, 57, 58, 60, 63, 66, 15, 18, 19, 21, 22\}$, as indicated by grey dots in Figure 4.9 (b) and (c), have an average increment of 2 – 8 Wh energy usage per congested ϑ for TALiSMaN with predictive control scheme compared to TALiSMaN.

For both schemes, the TEC indicates similar trend during operation hour 23:00-04:00 in Figure 4.9 (a) and during non-congested ϑ, as shown in Figure 4.9 (b) and (c). The reason is because the streetlights resume normal TALiSMaN operation when non-congested road traffic is predicted (see Section 3.5).

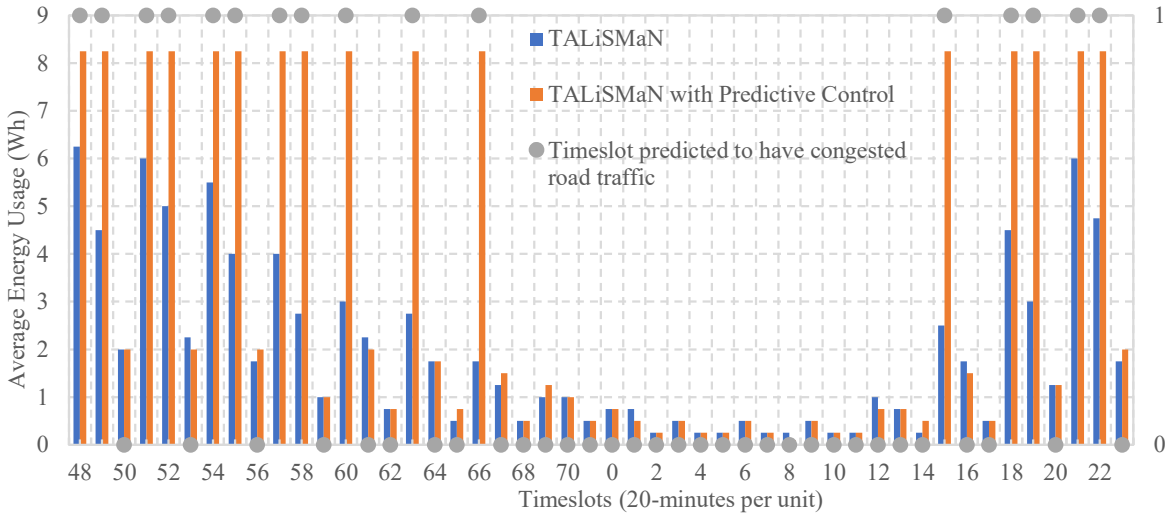
Both linear network topology as shown in Figure 4.4 (a) and cross-junction network topology as shown in Figure 4.9 (a) show similar trend of higher average TEC for operation hours with high road traffic volume. The surge of TEC for all scenarios at operation hour 16:00 to 22:00 and 05:00 to 07:00 are due to the application of $w = 20$ minutes causes entire 20 minutes turn on in full brightness when the ϑ is expected to be congested period. As compared to TALiSMaN, which only lights up for less than 1 minute for the same scenario, TALiSMaN with predictive control consumes more energy throughout the whole night due to longer turn on period. This, however, is consistent with the proposed TALiSMaN with predictive control.



(a) 438 and 3508 road traffic throughout streetlight operation hour



(b) 438 throughout various timeslots, ϑ



(c) 3508 throughout various timeslots, ϑ

Figure 4.9: Simulation reults showing the mean TEC of the streetlights while operating TALiSMaN and TALiSMaN with predictive control schemes under cross-junction network topology at different road traffic volume of (a) 438 and 3508 road traffic per day throughout streetlight operation hour; whist (b) 438 and (c) 3508 are for the 20-minutes interval ϑ. The timeslots that are predicted to have congested road traffic are indicated with grey dots.

4.6.4 Usefulness of the Streetlights

Figure 4.10 shows the streetlight usefulness experienced by road traffic when operating on TALiSMaN and TALiSMaN with predictive control schemes under different road traffic volume in the cross-junction network topology. In overall, TALiSMaN with predictive control improves, the usefulness of the streetlight during heavy road traffic scenarios, when compared to TALiSMaN.

Based on Figure 4.10, the average improvement in streetlight usefulness for 438 road traffic per day is 0.2% - 0.7%, ranging from 92.1% – 93.0%, whereas the average increase for 3508 road traffic per day is 0.1% – 0.5%, ranging from 91.9% – 92.7%. The usefulness of the streetlight provided by the proposed scheme maintained the same as TALiSMaN for

438 road traffic volume at operation hour 23:00 to 04:00 since the operation reverts to normal TALiSMaN for light road traffic scenario, as indicated in Section 3.5.

Since the usefulness of streetlight aids in extending the visual range of road users beyond that given by vehicle headlights, the 0.1% increment streetlight usefulness can provide better road user vision to prevent accidents and make night travels more comfortable. All human lives are valuable, thus, even a modest improvement in the usefulness of streetlights is crucial in this study, as it can make a significant impact on people's lives.

Although the proposed scheme consumes more energy compared to TALiSMaN, but the capability to lower PDR at rush hour, while improves the usefulness of the streetlight experienced by road user during heavy road traffic scenarios. Note that, the high average TEC is due to the prediction window size chosen, causing longer turn on period. This indicates that implementation of predictive control into TALiSMaN is a viable strategy to improve the packet dropped issue during heavy road traffic period.

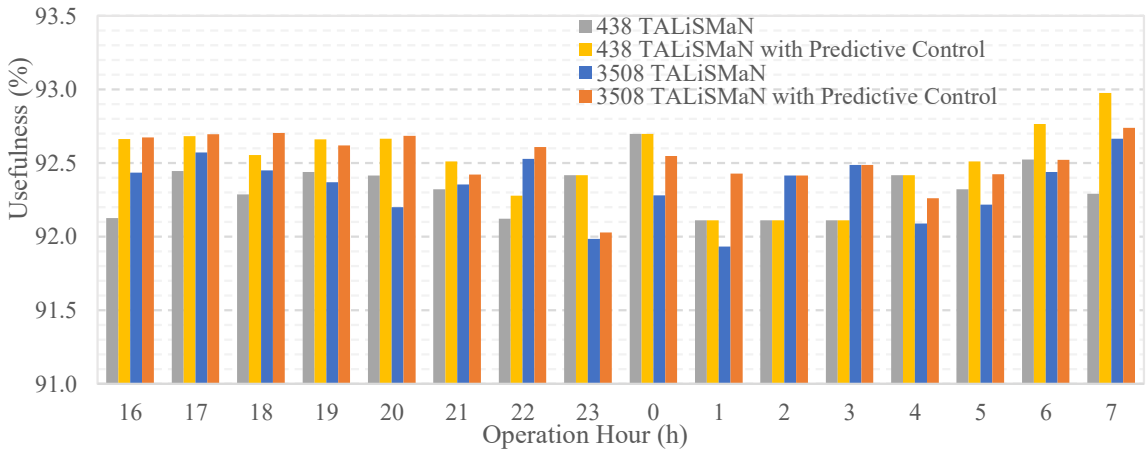


Figure 4.10: Simulation reults showing the average usefulness of the streetlights received by the simulated motorists under TALiSMaN and TALiSMaN with predictive control schemes in 438 and 3508 road traffic volume per day for cross-junction network topology.

4.7 Summary

This chapter presented the implementation and analysis of TALiSMaN with predictive control scheme. Before delving into details of the implementation, assumptions have been made for this simulation, followed by, the details of the simulation setups and a brief description of the evaluation parameters. Then, the proposed scheme, along with SMA road traffic estimator is evaluated in two case scenarios. In Case Study A, the performance of TALiSMaN with predictive control scheme for two different road traffic volumes is compared with TALiSMaN scheme based on the PDR, TEC and usefulness of the streetlight when simulated on linear network topology. From the simulation results, the PDR, TEC, and usefulness of the streetlight were directly proportional to road traffic volumes. When the residential road is packed with 3508 road traffic throughout the whole night, which represent 75% of road traffic for a year. These heavy road traffic flow triggered the network congestion and packet dropped issues in TALiSMaN scheme; thus, the proposed scheme provided a predictive control solution that averagely reduced the PDR by 0.01% – 5.6% and improved the usefulness of the streetlight by 0.1% – 2.9% but increased 0.75 – 15.75 Wh more TEC than TALiSMaN.

The execution of TALiSMaN with predictive control is further evaluated in Case Study B, where cross-junction network topology was adopted. The simulation results revealed that the PDR was doubled due to a higher concentration of sensor node at the intersection of the cross-junction topology compared to the linear topology. This has showed that predictive control is needed in TALiSMaN scheme. Based on the analysed results, the PDR for TALiSMaN with predictive control scheme is reduced by 0.04% – 6.28% and the usefulness of the streetlight is improved by 0.1% – 0.7% on average, but the TEC is increased by 0.25 – 15.75 Wh throughout the night, as compared to TALiSMaN.

Although the average results showed trivial PDR improvement, the PDR during congested road traffic timeslot, example at $\vartheta = 48$ showed exceptional improvement for TALiSMaN with predictive control scheme. Based on the results, the TALiSMaN with predictive control scheme experienced 12.9% to 37.4% PDR reduction depending on the traffic volume and streetlight network topology as presented in Section 4.5 and 4.6.

To recap, even though TALiSMaN with predictive control is not the optimum solution to the limitations of TALiSMaN, but the simulation results signify that it can decrease the PDR of the streetlights during heavy road traffic period while improve the usefulness of the streetlights experienced by the road users during heavy road traffic scenarios.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Introduction

This thesis discusses the issue of packet dropped and network congestion during data transmission of TALiSMaN in road traffic peak period, which may result in streetlight unable to operate as intended. The main aim of this research is to address the issue of uncontrolled increment of data broadcasting in TALiSMaN during rush hour or heavy road traffic flow period, which is due to the nature of flooding routing protocol adopted. Therefore, this study attempts to reduce the packet drops and network congestion issue during road traffic peak hour. This section summarises the contribution of this research in achieving the goal and objectives of this study. Furthermore, the potential future works are described based on the limitation of this study.

5.2 Achievements

With the advent of smart city that embedded with smart technology, namely smart streetlight, in urban development, the quality of living for citizens has been vastly improved. In Section 2.2, various networked street lighting schemes have been reviewed. Among those schemes, TALiSMaN scheme has shown to be one of the apt smart streetlight schemes to date. However, as discussed in Chapter 1, network congestion and packet drop issues existed in TALiSMaN scheme due to the nature of flooding routing protocol adopted. Flooding routing protocol is simple, yet adequate to perform data communication among sensor nodes. Thus, TALiSMaN adopted refined flooding routing protocol since the performance analysis of the routing protocol was not the focus of the existing research. However, the downside of the refined routing protocol only occurs during road traffic peak hour, which produced the

rate of 23% to 29% packet dropped due to congested network as highlighted in Section 2.3. Moreover, the severity of network congestion in TALiSMaN scheme that caused packets to drop was explained in Section 2.3, as it could lead to failure to turn on or off the streetlights when the required signal was not received. Additionally, this issue also leads to decrease of energy efficiency as the TEC in generating, receiving the packet, and waiting for recovery route process were wasted when network is congested that cause constant packet dropped (Katti & Lobiyal, 2021).

As mentioned in Chapter 2, a more popular approach is adopting routing protocols in tackling the issue of network congestion. After reviewing a list of existing works, which include energy-efficient, cluster and grid-based, congestion detection and control routing protocols. It was found that those were not suitable nor feasible to be implemented in TALiSMaN scheme due to several factors discussed in Section 2.4.3 and Section 2.4.4. One of the factors was the alternative path or dedicated path approach, which was not suitable on linear network topology, where all nodes were required to receive the signal to fulfil road traffic needs. The second factor was that the reviewed systems required a centralised system to process data at the base station, where every sensor node processed the data received when operated with TALiSMaN scheme. Lastly, periodic broadcast of control messages may increase the possibility of network congestion.

With these findings in mind, the study was then further explored the possibility of predictive model application in a TALiSMaN scheme to ease the network congestion issue. The idea was to use the prediction model to anticipate the incoming traffic condition. Then TALiSMaN scheme broadcasts the message to toggle each streetlight, according to the prediction result. Various types of prediction models, comprising of high complexity and

low complexity prediction tools were reviewed in Section 2.5. The high complexity predictors include ARIMA and machine learning approaches, can produce significant results but the learning curve is steep (Barga et al., 2015) to acquire within a short period of this research, and it requires a vast amount of computing resources to execute (Janke et al., 2016). The low complex online predictors were considered due to the limitation of WSN adopted in TALiSMaN scheme.

Chapter 3 proposed the TALiSMaN with predictive control scheme to address the network congestion issue in TALiSMaN scheme during rush hour. This scheme is TALiSMaN enhanced with road traffic predictor. This study considered three real-time short-term predictions, namely SMA, EMA and WMA, for TALiSMaN with predictive control scheme. Among these predictors, SMA was chosen based on prediction accuracy, prediction parameters, computing resource and complexity discussed in Section 3.6. To reduce packet dropped during road traffic peak period, firstly the prediction model estimated upcoming traffic condition based on the historical traffic data obtained, then the scheme compared the estimated traffic volume against the previous day of the week average traffic volume.

The performance of the TALiSMaN scheme implemented with SMA predictor was assessed with two case studies, which include linear and cross-junction topologies, as presented in Chapter 4. Both case studies have evaluated and compared the performance of TALiSMaN with predictive control scheme against TALiSMaN scheme under high and low road traffic volume per day scenarios, in terms of the PDR, TEC and streetlight usefulness experienced by road traffic. In Case study A: Linear Network Topology, the simulation was performed with linear network topology. The performance of TALiSMaN with predictive

control showed an average 0.01% – 5.6% reduction for PDR but averagely increased 5 – 15.75 Wh more of TEC while improved the usefulness of the streetlight by 0.1% – 0.4%, during road traffic peak period as compared to TALiSMaN at low road traffic count of 438 road traffic per day scenario. Whereas for high road traffic of 3508 road traffic per day scenario, the performance of TALiSMaN with predictive control at peak period revealed an average 0.17% – 4.85% reduction in PDR but 0.75 – 12.25 Wh more increment of TEC, while 0.1% – 2.9% improvement of streetlight usefulness experienced by the road users, as compared to TALiSMaN scheme.

For Case Study B: Cross-Junction Network Topology, the simulation was carried out with cross-junction topology for different traffic volume. Even though TALiSMaN with predictive control scheme averagely increased 4.5 – 15.75 Wh of TEC but achieved an average of 0.04% – 6.28% reduction for PDR while 0.2% – 0.7% improvement of the streetlight usefulness experienced by road users throughout the night, as compared to TALiSMaN scheme in low road traffic (438 per day) scenario. As for high road traffic (3508 per day) scenario, the proposed scheme averagely reduced 0.79% – 4.57% of PDR while improved the streetlight usefulness by 0.1% – 0.5% but required additional 0.25 – 9.75 Wh energy on average throughout the night, as compared to TALiSMaN scheme.

Although both case studies showed insignificant reduction in PDR, but the proposed scheme showed significant PDR improvement when evaluated throughout the timeslots, ϑ for all simulations. Based on the performance analysis, TALiSMaN with predictive control scheme did not encounter PDR and consumed at most 8.25 Wh TEC for predicted road traffic congested ϑ, as compared to TALiSMaN scheme for all network topologies with different road traffic volumes. The reduction of PDR during predicted road traffic congested ϑ for

proposed scheme is in fact dependant on the number of packets sent from TALiSMaN scheme at that ϑ.

In overall, streetlights experienced more PDR at the intersection for Case Study B was due to the density of the streetlight. Imaging that, one passing-by vehicle is detected by multiple streetlights in a short period of time, as compared to passing-by vehicle in linear streetlight networks. High density sensor node is prone to network overload issue, thus increase in packets drop. The streetlights incorporated TALiSMaN with predictive control scheme is expected to consume more energy at heavy road traffic flow operation hour for all scenarios because the streetlights turn on for the entire 20 minutes when congested road traffic is predicted, as described Section 4.5.3.

From the analysis of TALiSMaN with predictive control, it shows that the study has achieved the goal and objectives as intended. The reduction of PDR showed this study has successfully reduced the network congestion for TALiSMaN under heavy road traffic scenarios while improved the streetlight usefulness experienced by the road users.

The achievements of this study are as follows:

i. This study has evaluated and discussed the severity of network congestion in TALiSMaN throughout the streetlight operating hours in Section 2.3.

ii. The proposed congestion control scheme utilises a simple real-time prediction model, which is SMA to significantly improved the performance of TALiSMaN respectively during peak traffic periods. The implementation of the proposed scheme is described in detail in Section 3.6.

iii. This study also benchmarked the proposed solution in terms of PDR, TEC, and utility of the proposed scheme against TALiSMaN scheme in Section 4.5 and Section 4.6.

5.3 Future Works

Although this study has successfully achieved the goal stated in Section 1.4, there are several future works can be investigated to improve the proposed lighting scheme further. The future works are described as follows:

i. To consider different prediction windows for different density of streetlights. This research produced high PDR and TEC at specific low traffic operation hours that is from 23:00 to 04:00. The increase in PDR is due to a higher density of sensor nodes at the intersection road, where every node broadcast data to every adjacent node within limited buffer capacity, causing more packets to drop. The reason for high TEC is caused by a longer turn on period of the streetlight. Since congestion condition is determined every 20 minutes, one of the 20 minutes period from 22:00 to 23:00 may be considered as congested. As a result, the streetlights are required to turn on for 20 minutes, which is higher than normal turn on period when operating with TALiSMaN (less than 1 minute if car travels across 200 m at the speed of 40 kmh), that caused the increase in TEC. Thus, different prediction windows for different density of streetlights can be intensively investigated to avoid frequent dimming issue and reduce PDR and TEC. However, one should that note that the prediction computation time should be shorter than the turn on period, to ensure sufficient time to perform traffic prediction.

ii. To consider more sophisticated traffic prediction model and factors that can affect the prediction of road traffic. Since traffic prediction existed a decade ago, several advance traffic prediction tools that consider the occurrence of various events throughout the year for prediction purpose, have been proposed or developed. The various events can include holiday traffic, working days traffic, school days traffic, traffic incident, weather conditions, density and speed of the vehicles and other factors that are associated with the prediction of traffic volume (Lv et al., 2014). However, restriction on computing resources in WSN needs to be considered. Hence, further research can be carried out on these advance prediction tools and factors that have a relationship in traffic prediction. Since this research only based on the traffic profile obtained from Southampton City Council, the prediction performance and accuracy might vary when deploy on real-life scenarios.

iii. To evaluate the performance of proposed approach with different network topologies. This study only considers two different topologies, namely linear and cross-junction topology, to investigate the effect of PDR on TALiSMaN with and without prediction control. Although the PDR have successfully reduced for rush hour, but the performance of the lighting scheme may differ when different topology applied. Hence further investigation is required for various topologies, especially for topology that consists of streetlights that are group together in different section. These topologies include Y-intersection, “fork” intersection, diamond interchange, jughandle etc. To improve PDR, different intersection or interchange topologies can be considered for future research.

iv. To deploy with various traffic volumes and actual road traffic with various type of road traffic to investigate the effect on the performance and practicality of the proposed approach. The current approach was evaluated with average road traffic profile and two road traffic volumes obtained from Southampton City Council (European Platform on Mobility Management, n.d.), which may not be inadequate for deployment. The proposed approach could be extended to cover various road traffic scenarios to further improve the efficiency of the TALiSMaN with predictive control scheme.

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APPENDICES

Journal Publications

1. **Lee, P. Z.,** Lau, S. P., & Tan, C. E. (2019). Predictive Control for Distributed Smart Streetlight Network. *International Journal of Advanced Computer Science and Applications*, *10*(12), 328-335. doi: 10.14569/IJACSA.2019.0101244