



Quality-of-Service Aware Resource Allocation for Integrated Fiber-Wireless (FiWi) Access Networks

A THESIS
SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
DEGREE OF
Doctor of Philosophy

BY
Akshita Gupta

PhD19101

under the guidance of
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To my family...



Indraprastha Institute of Information Technology-Delhi

Okhla Industrial Estate, Phase III

New Delhi-110020, India

December-2023

Certificate

This is to certify that the thesis titled **Quality-of-Service Aware Resource Allocation for Integrated Fiber-Wireless (FiWi) Access Networks** being submitted by **Akshita Gupta** to the Indraprastha Institute of Information Technology-Delhi, for the award of the degree of **Doctor of Philosophy**, is an original research work carried out by her under our supervision. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree. The results contained in this thesis have not been submitted in part or full to any other university or institute for the award of any degree/diploma.

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The study pertaining to this dissertation has not been submitted in part or in full, to any other University or Institution for the award of any other degree.

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A handwritten signature in black ink, appearing to read 'Akshita Gupta', with a stylized flourish at the end.

Akshita Gupta

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ABSTRACT

This thesis aims to propose an efficient resource allocation framework to ensure the quality of service (QoS) to the users. The frameworks proposed in this dissertation can be efficiently utilized to provide QoS guarantees by efficient resource allocation not only in the static FiWi network scenarios but also for the mobile vehicular networks. Specifically, this thesis is structured into four sections, namely energy resource allocation for green FiWi networks, QoS aware high throughput FiWi network, latency reduction in FiWi-based vehicular networks, and emergency path planning for safe-driving in transportation Metaverse (TransVerse). The first section of this dissertation analyzes the techno, socio, and economic impact of energy resource allocation and provides 24×7 services to the users. In order to do so, we utilize a 3rd generation partnership project (3GPP) based model to generate the user request at the optical network unit (ONU) and access point (AP) collectively known as ONU-AP. These requests were used to calculate the load of the ONU-AP and further model the energy requirement, as well as allocate energy resources to provide 24×7 services to the users. In the second section, we extend the above work by utilizing the last 10 years' data on available solar power to predict the amount of solar power that can be generated on a particular day. This would reduce the amount of charging and discharging cycles that are required by the battery and would improve the lifetime of the batteries. In a communication network, maintaining the latency and reliability requirements along with throughput is also crucial. Consequently, the second section of the thesis utilizes key performance indicators (KPIs) such as latency, reliability, and data rate based classification to classify the data traffic at the APs into different services, such as voice, video, and best-effort traffic. Based on this classification, the data traffic is assigned to different traffic containers (T-CONTs) of the PON. Depending on the KPIs, a priority-based bandwidth allocation scheme is designed to improve the QoS

of the users.

Moreover, during high mobility scenarios, meeting the QoS requirements becomes all the more difficult. Thus, the later part of this thesis extends the QoS guarantees for connected vehicular networks. Consequently, an integrated next-generation passive optical network 2 (NG-PON2) and IEEE 802.11p-based vehicle-to-infrastructure (V2I) network is proposed to facilitate the stringent requirements of sixth-generation (6G) vehicular networks. This work minimizes the latency of the FiWi-based V2I network by utilizing a machine learning (ML) based T-CONT priority assignment wavelength allocation algorithm that minimizes the number of wavelength switching instances in the PON, subsequently reducing the latency of the network. We further improve the performance of vehicular network by utilizing vehicle-to-vehicle (V2V) services along with V2I services. This requires the selection of an optimal cluster head for the offloading of V2V traffic. In order to do so, we utilize a double deep Q network (DDQN)-based cluster head selection policy to select the cluster head to minimize the energy and latency of the vehicular network.

Furthermore, as a part of 6G network, the research community has been recently focusing on emerging technologies such as digital twins (DTs), blockchain, extended reality, etc. Thus, in the last section, we exploit a transportation Metaverse (TransVerse)-enabled vehicular network to offload real-world vehicular data traffic to the vehicular cloud network and allocate physical and virtual resources in the network. We consider a pre-emptive emergency situation and formulate a utility-to-cost ratio optimization problem to minimize the collision risk along with the latency and computation cost of the network. Further, we utilize the prior information processing in the DT-enabled vehicular traffic to enhance the lane-change experience of the users.

The frameworks proposed in this dissertation can be efficiently utilized to provide QoS guarantees by efficient resource allocation not only in the static FiWi network scenarios but also for the mobile vehicular networks. This will be helpful for a communication

engineer to design a sustainable system that exploits new technologies, such as DT-enabled Metaverse, to guarantee the required QoS to the end users.

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ABBREVIATIONS

3GPP	3rd generation partnership project
4G	Fourth generation
5G	Fifth generation
6G	Sixth generation
10G-EPON	10-Gigabit ethernet passive optical network
AC	Access category
ACC	Adaptive cruise control
AI	Artificial intelligence
AIFS	Arbitration inter-frame spacing
ANN	Artificial neural network
AP	Access point
AR	Augmented reality
AWG	Arrayed-waveguide grating
BE	Best effort
BS	Base station
C-V2X	Cellular-V2X
CO₂	Carbon dioxide
CAPEX	Capital expenditure
CART	Classification and regression tree
CAV	Connected and autonomous vehicle
CDC	Coded distributed computing
CNP	Context-aware navigation protocol
CPS	Cyber–physical systems
CPSS	Cyber–physical-social systems
CRV	Collision risk vehicles
DAO	Distributed autonomous organization

DBA	Dynamic bandwidth allocation
DBWA	Dynamic bandwidth and wavelength allocation
DDQN	Double deep Q network
DCF	Distributed coordination function
DHI	Diffuse horizontal irradiation
DIL	Driver-in-the-loop
DNI	Direct normal irradiation
DoD	Depth of discharge
DRL	Deep reinforcement learning
DT	Digital twin
DTMC	Discrete-time Markov chain
e2e	End-to-end
EDAS	Eco-driving assistance system
EDCA	Enhanced distributed channel access
E-PON	Ethernet passive optical network
EPON-WiMax	EPON-WiMax
ETSI	European telecommunications standards institute
FiWi	Fiber-wireless
FTTH	Fiber-to-the-home
G-PON	Gigabit passive optical network
GDR	Guaranteed data rate
GHI	Global horizontal irradiance
GMM	Gaussian mixture model
HCRV	High collision risk vehicle
IG	Information gain
IoM	Internet of Minds
IoT	Internet of Things

IoV	Internet of vehicle
IS	Interstate
ISAC	Integrated Sensing and Communication
ITS	Intelligent transport systems
ITS-G5	Intelligent transport systems-5th generation
ITU-T	International Telecom Union-Telecommunication Standardization Sector
KPI	Key performance indicator
LOR	Latency outage rate
LSTM	Long short-term memory
LTE	Long term evolution
LTE-V2X	Long-term evolution-vehicle-to-everything
MAC	Media access control
MAE	Mean absolute error
MEC	Mobile edge computing
ML	Machine learning
MR	Mixed reality
MSE	Mean square error
MSP	Metaverse service provider
NG-PON	Next generation-PON2
NN	Neural network
NS-3	Network simulator-3
OFDM	Orthogonal frequency division multiplexing
OLT	Optical line terminal
ONU	Optical network unit
ONU-RSU	Optical network unit-roadside unit
pdf	Probability distribution function
PLR	Packet loss rate

PON	Passive optical network
PPBP	Poisson Pareto Burst Process
PV	Photovoltaic
QCLP	Quadratic constraint linear programming problem
QCQP	Quadratic constraint quadratic programming problem
QKD	Quantum key distribution
QoS	Quality of service
RAN	Radio access network
RF	Radio frequency
RIS	Reconfigurable intelligent surface
RL	Reinforcement learning
RSU	Road side unit
SoC	State of charge
SDR	Surplus data rate
SNR	Signal-to-noise ratio
SUMO	Simulation of urban mobility
RMSE	Root mean square error
SDN	Software-defined networking
T-CONT	Transmission containers
TD	Temporal difference
TDM	Time division multiplexing
TDMA	Time division multiple access
TMY	Typical meteorological year
TransVerse	Transportation Metaverse
TSTP	Trustful space-time protocol
TWDM	Time and wavelength multiplexing
UAV	Unmanned aerial vehicle

UE	User equipment
URLLC	Ultra reliable low latency communication
V2I	Vehicle-to-infrastructure
V2N	Vehicle-to-network
V2P	Vehicle-to-pedestrian
V2V	Vehicle-to-vehicle
V2X	Vehicle-to-everything
VANET	Vehicular ad hoc network
VCEC	Vehicular collaborative edge computing
VI	Video
VECN	Vehicular edge collaborative networks
VEC	Vehicular edge computing
VFC	Vehicular fog computing
VFN	Vehicular fog network
VO	Voice
VR	Virtual reality
WAP	WiFi access point
WiFi	Wireless fidelity
WiMax	Worldwide interoperability for microwave access
WLAN	Wireless local area network
WMN	Wireless mesh network
WSS	Wavelength selective switches
XG-PON	10-Gigabit-capable passive optical network
XR	Extended reality

NOTATIONS

$\epsilon(t)$	Action selection probability in ϵ -greedy policy
A_t	Action taken during time slot t
$Q_\pi(S, A)$	Action value function for state S and action A
x_a	Actual value
ρ_a	Air density
$B_{n,k}$	Allocated bandwidth to the V2V channel
f_k^n	Allocated CPU clock speed at cluster-head vehicle k to task ϕ_n
$W_{n,k}^{bac}(t)$	Amount of feedback data transmitted after the processing of tasks at cluster-head vehicle at time slot t
$W_n^{off}(t)$	Amount of tasks leaving V_n task offloading queue at time slot t
$W_n^{loc}(t)$	Amount of tasks offloaded at time slot t
$W_{n,k}^{com}(t)$	Amount of tasks processed by cluster-head vehicle at time slot t
a_i	Amplitude of the i^{th} peak in data series
θ^s	Angle of incidence of the beam
C_{PV}^{asset}	Asset cost of PV panel
C_B^{asset}	Asset cost of battery
C_W^{asset}	Asset cost of wind turbine
$f_n(t)$	Assigned CPU frequency to the V2I offloading tasks at t^{th} time slot
$f_{n,k}(t)$	Assigned CPU frequency for executing the offloaded task at the cluster-head vehicle at t^{th} time slot
$U_{v,i}$	Association of vehicle v with the i^{th} RSU
λ_{NS}	Assured to non-assured bandwidth ratio for T-CONT 3.
B_f	Available bandwidth from the backhaul fiber network
N_2	Available set of vehicles generating T-CONT ₂ traffic
$Th(t)$	Average throughput at hour t
B	Bandwidth

P_B^{cap}	Battery capacity
c_k^n	Binary variable indicating the offloading of task ϕ_n to k^{th} vehicle at t^{th} time slot
$c_k^i(t)$	Binary variable that represents whether i^{th} vehicle has a task to be offloaded to k^{th} vehicle
R_w	Blade radius of wind machine
$\lceil \cdot \rceil$	Ceiling function
$h_{n,k}$	Channel gain
n_c	Child vehicle
P_{col}	Collison probability
κ	Computation power parameter
T_{ij}^{tr}	Communication latency link between vehicle i and RSU j
f_c	Computation capabilities
d_i	Computational data of i^{th} vehicle
d_i'	Computational data transferred by RSU to adjacent RSU
f_{ij}^e	Computation resource allocated by RSU j to vehicular tasks of i^{th} vehicle
c_i	Computation resources required by digital twin of i^{th} vehicle
D_u	Computation result of each task
ζ	Constant close to zero
Γ^c	Constant representing the weightage of computation resources of the vehicle
Γ^t	Constant representing the weightage of end-to-end latency of the vehicle
C_B	Cost of battery
C_{PV}	Cost of PV panel
γ_{gx}	Cross-factor of the packets generated by the application
γ_{xr}	Cross-factor of the packets at reception

$CB_{i,k}$	Cut-off for the total number of T-CONTs of type ‘ k ’ in i^{th} wavelength bin
$d^i(t)$	Data size of the offloading task ϕ_i at t^{th} timeslot
Deficit-BW	Deficit bandwidth
D_{ONU_j}	Latency at j^{th} ONU in 12 hours
$D_k^{\mathbf{T-CONT}}(t)$	Latency of the k^{th} T-CONT at time t , where $k \in [2, 5]$
D_{oh}	Latency due to overheads at the ONU
$D_k^{\mathbf{th}}$	Latency threshold of k^{th} T-CONT
β	Depth of discharge factor =30%
P_a	Denotes whether the battery level is beyond DoD
ϑ	Deviation in velocity
v_i^d	Desired velocity of the vehicle for lane changing
D_H	Diffuse horizontal irradiance (DHI)
γ_{DF}	Discount factor
$d_{n,k}$	Distance between task vehicle and cluster-head vehicle
D_N	Direct normal irradiation (DNI)
δ_d	Downstream data rate at ONU-AP
R_{ij}^{dl}	Downlink communication rate between vehicle and RSU
B_d	Downlink bandwidth
D_{O_j}	E2e latency for the optical link
S^*	Emergency driving decisions
T_i^{e2e}	End-to-end latency for communication, computation, and reaction latency
T_i^{e2e}	End-to-end latency required for communication and computation of the vehicular tasks
$E_n^{off}(t)$	Energy consumed by the task during V2V offloading process at time slot t
$E_n^{com}(t)$	Energy consumed during the computation of task at the cluster-head at time slot t
$E_n^{bac}(t)$	Energy consumed while sending the task ϕ_n result feedback at time slot t

$E^{loc}(t)$	Energy consumption required for the local processing of tasks at time slot t
$H(X)$	Entropy of random variable X
χ_v	Estimation accuracy
$\mathcal{A}, \mathcal{B}$	Estimators in DDQN algorithm
d_{euc}	Euclidean distance
$P_{excess}(t)$	Excess solar power available at the PV panel at t^{th} hour
V_π	Expected discount return
P_T^S	E2e link reliability for all the T-CONTs of the FiWi-based V2I network
y_e	Exponentially distributed random variable
$\mathcal{N}$	Gaussian random variable
Grant-size	Granted bandwidth
t	t^{th} hour of the day
T_H	Hour of the day for off-grid scenario when we consider the batteries should be entirely charged
$P_S^M(t)$	Hourly solar power profile of a M PV panels at t^{th} hour
P_{idle}^{AP}	Idle mode power consumption of the AP
$\mathbb{1}(\cdot)$	Indicator function
D_l	Input data size of each task
$U_n^{T_2}$	Latency based utility function for T-CONT ₂
$D_n^{com}(t)$	Latency during the computation of task at the cluster-head at time slot t
$D^{loc}(t)$	Latency for the local processing of tasks at time slot t
$D_k^n(t)$	Latency for task ϕ_n traffic
$D_n^{off}(t)$	Latency of the task during V2V offloading process at time slot t
τ	Latency threshold for the vehicular tasks
$D_n^{bac}(t)$	Latency while sending the task ϕ_n result feedback at time slot t
$G_{n,k}^{com}(t)$	Stored offloaded tasks at t^{th} time slot

δ_r	Learning rate
L	Length of the road segment
$Q_n^{loc}(t)$	Local task offloading queue at time slot t
L_i	Location of the centroid of the i^{th} peak in data series
L^{DDQN}	Loss function for DDQN
Δt	Maueuver Time
$R_k(\Gamma_v, L_v, \epsilon)$	Maximum achievable ergodic rate of the vehicle v
$AB_{\max}$	Maximum allocation bytes
F_k	Maximum CPU clock speed that can be allocated for local processing
h_{max}	Maximum headway between vehicles
N	Maximum number of batteries
M	Maximum number of PV panels
B_s	Maximum power of a single battery
C_{pmax}	Maximum rotor power coefficient of wind machine
v_{max}	Maximum velocity limits of the vehicle
$AB_{\min}$	Minimum allocation bytes
F_k^{min}	Minimum CPU clock speed that can be allocated for local processing
h_{min}	Minimum headway between vehicles
v_{min}	Minimum velocity limits of the vehicle
ϕ_n	n^{th} vehicular task
B_i	Normalized capacity of wavelength bin, i
$\Lambda_{\text{ONU-RSU}_j}(t)$	Normalized load of ONU-RSU $_j$ on a wavelength at time t
ϕ	Null set
N_{RSU}	Number of RSUs on the road
γ^h	Number of hours grid supply is available
N_B^{rep}	Number of times the batteries are needed to be replaced during the lifetime of the system

N_B	Number of batteries
N_{PV}	Number of PV panels
N_{WS}	Number of wavelength switching instances at the ONU-RSU
T_H	Number of time slots
$N_{ONU-RSU}$	Number of RSUs in the network
K	Number of vehicles to which RSU is connected
N_W	Number of wavelengths to be allocated to the ONUs
N_{train}	Number of training steps
N_{eval}	Number of evaluation steps
N_{nodes}	Number of nodes in the network
FB	Number of bytes in a frame.
N_L	Number of hops in left lane
N_R	Number of hops in right lane
N_4	Number of users with BE traffic.
N_2	Number of users with voice traffic.
N_3	Number of users with video traffic.
$c_k^n(t)$	Offloading of task ϕ_n to k^{th} vehicle at t^{th} time slot
$C_B^{O\&M}$	Operation and management cost (O&M) of the battery
$C_W^{O\&M}$	Operation and management cost of the wind turbine
$C_{PV}^{O\&M}$	Operation and management cost of the PV panels
$D_{o,s}$	OLT-splitter distance
$D_k^O(t)$	Optical latency of k^{th} T-CONT traffic at time t
n_p	Parent vehicle
P_{em}	Planned emergency path
P_{NS}^{ONU-AP}	Power demand of ONU-AP when solar energy is not available
P_S^{ONU-AP}	Power demand of ONU-AP when solar energy is available
N_0	Power of Gaussian white noise

P_{sa}	Power consumption of sleep aware ONU
P_{af}	Power consumption of active free mode of ONU
P_{ah}	Power consumption of active held mode of ONU
P_{as}	Power consumption of asleep mode of ONU
P_{da}	Power consumption of doze aware mode of ONU
P_{ls}	Power consumption of listen mode of ONU
$P_{ONU}(t)$	Power consumption profile of ONU at t^{th} hour
$P_{BAT}(t)$	Power supplied by the battery to the ONU at t^{th} hour
$P_{grid}(t)$	Power supplied by the grid to the ONU at t^{th} hour
$B_{state}(t)$	Power level of the battery at t^{th} hour
x_p	Predicted value
$p_i(t)$	Price for i^{th} vehicle at t^{th} time slot.
$p_n C_n$	Price paid for task ϕ_n
P_{RSU}^F	Probability of failure of RSU
P_{V2I}^F	Probability of failure of V2I link
P_V^F	Probability of failure of vehicle equipment
$p(x)$	Probability of x
T_p	Probability of each state of ONU, where $p \in \{sa, as, da, ls, af, ah\}$
$P_{ONU-OLT}^F$	Probability of failure of transmission from ONU to OLT
P_{ONU}^F	Probability of failure of ONU
P_{cong}^F	Probability of failure of transmission due to optical network congestion
P_C^F	Probability of fiber cut
γ_p^o	Probability of each state of ONU, where $p \in \{sa, as, da, ls, af, ah\}$
D_P	Processing latency
D_{tr}	Propagation latency
D_Q	Queueing latency
r_g	Rate parameter

R_b	Rate of transferring data to adjacent RSU
$\theta'_{k,n}$	Ratio of F_k^{min} to F_k if the cluster head decides to accept the V2V offloading requests from vehicle n
θ_k	Ratio of F_k^{min} to F_k
α	Ratio between solar power supplied to operate ONU-AP and to charge the batteries
$\{x_i(t), y_i(t)\}$	Rectangular coordinates of i^{th} vehicle
R	Reward function
$G_{n,k}^{bac}(t)$	Result feedback queue at time slot t
λ_n	Required computational density for a task
T_{Rx}^{AP}	Reception airtime percentage of AP
P_{Rx}^{AP}	Reception power of AP
RT	Reaction Time
ϵ	Reliability of wireless link
Remaining-BW	Remaining BW after granting bandwidth to voice and video traffic.
$\mathbf{R}(\cdot)$	Risk function
$\mathbf{R}^{ie}$	Risk for i^{th} vehicle in the emergency lane or the lane where the accident took place
r_{ab}	Road segment
S_i	Safe lane quality
S^L	Safe lane quality of left lane
S^R	Safe lane quality of right lane
$\mathbb{Z}$	Set of integers
$\mathcal{N}_{\text{ONU-RSU}_k^{\text{T-CONT}}}$	Set of ONU-RSUs with T-CONT k traffic
Γ_v	SINR at v^{th} vehicle
$P_{PV}(t)$	Solar power allocated to the ONU at t^{th} hour
S_t	State space during time slot t

$\Gamma_{n,k}$	SNR of the wireless channel
$\mathbf{D}_{s,ONU}$	Splitter-ONU distance
$\mathcal{S}_i(t)$	State information of i^{th} vehicle
$Q_n^{off}(t)$	Task offloading queue at time slot t
T_i^{rsu}	Task execution time when vehicle i chooses to offload the task to the RSU
$\beta_n^{T_2}$	Tasks for T-CONT ₂ traffic
Threshold-BW	Threshold bandwidth
T_c	Time-to-collision
T_{cmin}	Time-to-collision when a vehicle maximally accelerates toward the obstacle
T_{cmax}	Time-to-collision when a vehicle minimally accelerates toward the obstacle
Δ	Total available CPU clock speed
N_s	Total data samples
Total Deficit-BW	Total deficit bandwidth.
T_{total}	Total number of time slots
C_{PV}	Total operation cost for the PV panels
C_B	Total operation cost for the batteries
N_p	Total number of peaks in the data series
T_{Tx}^{AP}	Transmission airtime percentage of AP
η	Trade-off factor between energy and latency
$\lambda_u(t)$	Traffic request rate at hour t
P_t	Transmission power
$R_{n,k}$	Transmission rate between cluster-head and task vehicle
P_{Tx}^{AP}	Transmission power of AP
D_{tuning}	Tuning latency from one wavelength to the next
$\mathcal{U}_k^{loc}$	Utility of local tasks
$\mathcal{U}$	Utility for task ϕ_n
δ_u	Upstream data rate at ONU-AP

B_u	Uplink bandwidth
$XG - PON_{upstream}$	Upstream bandwidth of XG-PON
R_{ij}^{ul}	V2R uplink communication rate between RSU and vehicle
$\mathbf{N}$	Vehicle density
v_p	Velocity of parent vehicle
v_c	Velocity of child vehicle
v_i	Velocity of i^{th} vehicle
W_i	Width of peaks in data series
W	Width of the road
v_w	Wind speed
$D_k^{\mathbf{W}}(t)$	Wireless latency of k^{th} T-CONT traffic at time t

Chapter 1

Introduction

With the increasing development and deployment of telecommunication networks, there is a demand for ubiquitous and uninterrupted connectivity. Fiber-wireless (FiWi) network consists of fiber backhaul network with wireless fronthaul as shown in Fig. 1.1. It complements the benefits of standalone wireless and optical networks to provide a network that is flexible, reliable, and has high bandwidth. In general, FiWi network has a fiber backhaul network consisting of Gigabit-capable passive optical network (G-PON) with the upstream bandwidth of 1.25 Giga-bits-per-second (Gbps) and downstream bandwidth of 2.5 Gbps [1], or 10-Gigabit-capable passive optical network (XG-PON) with an upstream and downstream bandwidth of 2.5 Gbps and 10 Gbps [2], respectively. The fiber backhaul network may also constitute of IEEE 802.3ah/av 1/10 Gbps ethernet passive optical network (E-PON) [3], [4], or IEEE P802.3ca 25 Gbps EPON [5].

The wireless fronthaul network consists of various wireless standards such as, wireless fidelity (WiFi), worldwide interoperability for microwave access (WiMAX), long term evolution (LTE), fourth generation (4G)/fifth generation (5G) radio access network (RAN) [6]–[11]. Moreover, the demand for highly reliable services with ultra-low-latency and very high throughput can be met with the conceptualization of the next generation of mobile wireless networks. Specifically, for the case of vehicular data traffic where ensuring the safety and security of the vehicles with the use of critical functions, such as automatic emergency braking, driver assistance, collision warning, etc. the above demand is justified. The different modes of vehicular communication are defined in [12], namely vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), vehicle-to-

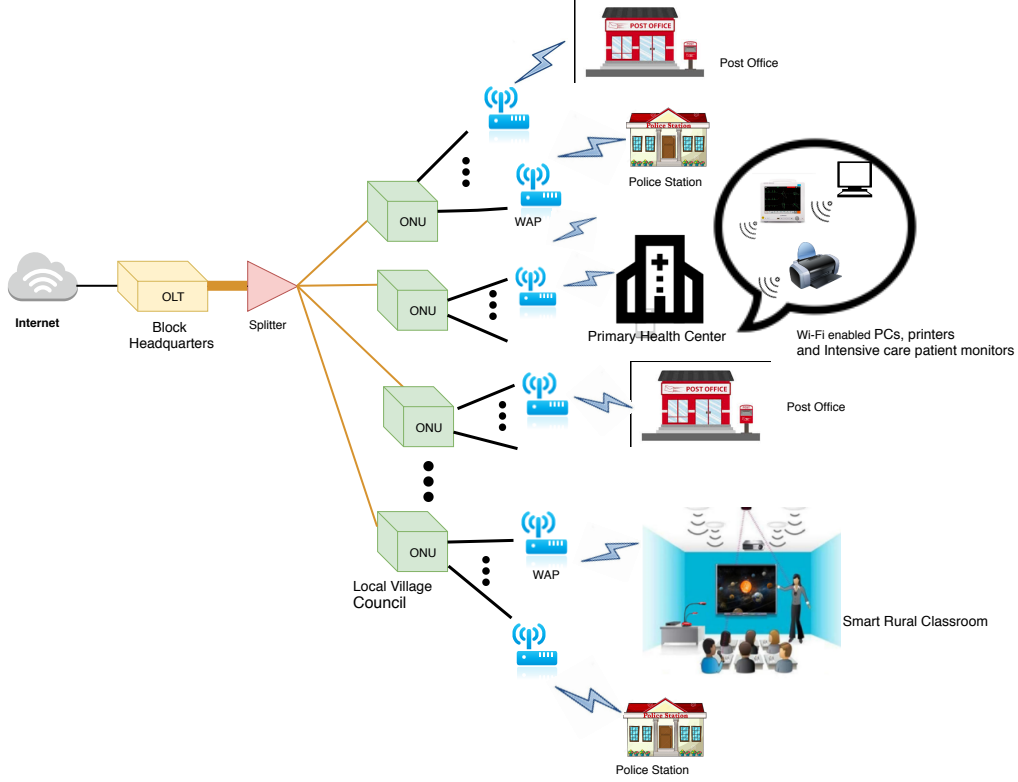


Figure 1.1: System Architecture of FiWi Network

network (V2N), etc. Intelligent transport systems-5th generation (ITS-G5) and long-term evolution-vehicle-to-everything (LTE-V2X) are the two most promising wireless technologies developed to cater to ITS services. ITS-G5 was proposed by the European telecommunications standards institute (ETSI). It is based on IEEE 802.11p (2012), while LTE-V2X, also known as cellular-V2X (C-V2X) is proposed by 3rd Generation Partnership Project (3GPP) [13]. In order to meet the demand for high throughput vehicular network with high reliability and low latency, mobile edge computing has emerged as one of the possible solutions [14], [15]. However, single communication technology cannot meet the ever-changing wireless communication requirements in highly dynamic vehicular networks [15]. Hence, FiWi networks which combine the advantages of fiber network such as high capacity, with the advantages of wireless network, such as mobility, flexibility, and ease of deployment, is emerging as one of the promising networking technology for sixth generation (6G) communication networks [14], [15]. FiWi-assisted vehicular com-

munication utilizes passive optical networks (PONs) as the backhaul along with vehicular network at the fronthaul to enhance the quality of service (QoS) for this network [15]. The authors in [16] utilized FiWi technology to minimize the processing latency of the vehicular computation tasks.

Moreover, the next-generation Internet exploits innovative information and communication technologies that merge the real world with its equivalent digital world to provide extremely interactive and fully immersive experiences to users. In this regard, several technologies have evolved that merge the physical and virtual worlds, including digital twin (DT), extended reality (XR) including virtual reality (VR), augmented reality (AR), and mixed reality (MR). DT technology generates a digital representation of physical objects and systems, creating a virtual counterpart that mirrors the real world with the objective of achieving real-time physical-virtual synchronization. This synchronization is facilitated through a continuous exchange of information between the virtual and physical realms, enabling the monitoring of changes in the real entity's condition and analyzing its effect in the digital realm. The DT-based connected vehicular network could ensure that the critical quality of service challenges posed by the vehicular network are met. The authors in [17] suggested that in comparison to the advancements witnessed in 4G and 5G wireless technologies, the emergence of DTs for diverse objects within the edge cloud emerges as a pivotal cornerstone in the landscape of the digital realm in the 6G epoch.

1.1 Objectives

The main objective of this thesis is to create an analytical framework to optimize the allocation of network resources in order to guarantee the QoS requirements of the users. This thesis talks about resources not only in terms of bandwidth and wavelength resources but also in terms of green energy resources. The resource allocation is done such that QoS requirements in terms of communication standards, such as International Tele-

com Union-Telecommunication Standardization Sector (ITU-T) and 3GPP standards, are maintained. Specifically, this dissertation has the following objectives:

1. To investigate the influence of location and throughput profile on the network resource requirements. Additionally, allocate renewable sources of energy, such as photovoltaic (PV) panels and batteries, to the network devices to mitigate the impact of erratic grid power supply and ensure 24×7 network connectivity.
2. Along with the throughput profile, meeting the latency and reliability requirements of the network data traffic is also essential. Thus, we design a data classification scheme taking into consideration these key performance indicators (KPIs). Thereafter, we propose a network resource optimization framework to allocate the network resources, such as bandwidth and wavelength, according to the priority of the data.
3. Thereafter, we extend the classification of network data traffic to the vehicular environment, where optimal spectral and communication resources allocations scheme is proposed to ensure the QoS requirement for future 6G connected vehicular networks.

1.2 Contributions and Research Outcomes

Some of the major contributions of the proposed work are summarized as follows:

1.2.1 Techno-Socio-Economic Impact of Joint Energy Resource Allocation Scheme in FiWi Network

To mitigate the conventional limitations of grid-power supply and provide a 24×7 connectivity to the users, an off-grid FiWi network is considered where the components of the network such as ONUs and IEEE 802.11 APs are powered using renewable sources of energy such as PV panels and wind turbines along with batteries. We propose a joint energy resource allocation framework to minimize the number of PV panels and batteries

required by ONU-AP. We provide a techno-socio-economic impact analysis of the energy resource allocation framework based on the energy resource requirement, the carbon dioxide (CO₂) emissions, and cost analysis of FiWi network. Moreover, a trade-off analysis between allocation efficiency and cost is also investigated. The publications based on the above work are:

1. Akshita Gupta, Vivek Ashok Bohara and Anand Srivastava, “Techno-Socio-Economic Impact of Joint Energy Resource Allocation Scheme in FiWi Network,” in IEEE Transactions on Network and Service Management, vol. 19, no. 2, pp. 1472-1488, June 2022, doi: 10.1109/TNSM.2022.3144996.
2. Akshita Gupta, Anand Srivastava, and Vivek Ashok Bohara, “Resource Allocation in Solar-Powered FiWi Networks,” in IEEE Access, vol. 8, pp. 198691-198705, 2020, doi: 10.1109/ACCESS.2020.3034685.

1.2.2 Energy Resource Allocation for Green FiWi Network Using Ensemble Learning

As the solar power profile generally differs for each day, thus energy resource allocation needs to be done such that the resources are neither under-utilized nor over-utilized. In order to allocate the energy resources at any specific location, it is essential to predict the solar power at that location. This work extends the previous work by utilizing a random forest regression-based ensemble learning to effectively predict the solar power available for the FiWi network components, such as ONU-APs. Thereafter, a joint energy resource allocation framework is proposed to minimize the required number of PV panels and batteries. To solve the joint energy resource allocation problem, we divide it into two sub-problems: minimum PV panel allocation for a fixed number of batteries and minimum battery allocation for a fixed number of PV panels. The two sub-problems are further solved using the proposed *MinBatAlloc* and *MinPVAlloc* algorithms. Moreover, we

introduce a system parameter α , which signifies the ratio between solar power supplied to operate ONU-AP and to charge the batteries. The variation of α impacts energy resource allocation along with the battery lifetime. Further, a comparative analysis of the proposed approach with non-ML based approaches is shown in terms of outage, lifetime, CO₂ emissions, and cost. This work resulted in the following publication:

3. Akshita Gupta, Halwai Sakshi Gupta, Vivek Ashok Bohara and Anand Srivastava, "Energy Resource Allocation for Green FiWi Network using Ensemble Learning," in IEEE Transactions on Green Communications and Networking, vol. 6, no. 3, pp. 1723-1738, Sept. 2022, doi: 10.1109/TGCN.2022.3164443.

1.2.3 Performance Evaluation of Integrated XG-PON And IEEE 802.11ac Based EDCA Networks

With the increase in demand for multimedia services and real-time applications, meeting the packet loss rate (PLR) and end-to-end latency requirements along with the throughput becomes necessary to meet the enhanced QoS of the users. In this work, we integrated FiWi network composed of a XG-PON and IEEE 802.11ac based wireless local area network (WLAN) to enhance the throughput of the FiWi network such that each user is granted an uplink data rate of 100 mega-bits-per-second (Mbps). Each user is assumed to transmit three kinds of traffic, i.e., voice, video, and best effort (BE). The voice traffic is given the highest priority, followed by video and BE. To enhance the QoS of the users, we propose a deficit dynamic bandwidth allocation (DBA) algorithm that makes effective use of channel bandwidth and allocates the unused bandwidth of the higher-prioritized services to low-priority service transmission containers (T-CONTs) dynamically. We examine the performance of the proposed algorithm to achieve an improvement in the QoS parameters like average throughput, end-to-end latency, PLR, and aggregate throughput within an acceptable range of ITU-T standards. Some of the publications that resulted

from the above work are:

4. Ravneet Kaur, Akshita Gupta, Anand Srivastava, Bijoy Chand Chatterjee, Abhijit Mitra, Byrav Ramamurthy, and Vivek Ashok Bohara, “Resource Allocation and QoS Guarantees for Real World IP Traffic in Integrated XG-PON and IEEE802.11e EDCA Networks,” in IEEE Access, vol. 8, pp. 124883-124893, 2020, doi: 10.1109/ACCESS.2020.3007778.
5. Akshita Gupta, Hritik Goel, Vivek Ashok Bohara and Anand Srivastava, “Performance Evaluation of Integrated XG-PON and IEEE 802.11ac based EDCA Networks,” 2020 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), 2020, pp. 1-6, doi: 10.1109/ANTS50601.2020.9342752.

1.2.4 Traffic Prediction Assisted Wavelength Allocation in Vehicle-to-Infrastructure Communication: A Fiber-Wireless Network Based Framework

The advent of the next generation of connected and autonomous cars offers immense opportunities for both users as well as service providers. In particular, FiWi based V2I network can facilitate some of the stringent requirements of 6G vehicular networks, including higher capacity, lower latency, and ubiquitous connectivity. FiWi based V2I network integrates the next generation-PON2 (NG-PON2) with IEEE 802.11p based V2I network. Similar to the previous work, we first review the various kinds of vehicular data traffic and their desired KPIs, namely throughput, latency, and reliability. Depending on the KPI requirements, the V2I traffic is classified among four classes and assigned to different T-CONTs of the ONU. Further, in order to minimize the latency of the network, we propose a machine learning (ML) based T-CONT priority assignment wavelength allocation algorithm that minimizes the number of wavelength switching instances in the PON. The performance of the proposed ML-based wavelength allocation algorithm is compared with

the other approaches, namely random and equal T-CONT based wavelength allocation algorithms, in terms of end-to-end (e2e) latency, throughput, and reliability. The above work led to the following publication:

6. Akshita Gupta, Abhishek Pratap Singh, Arunima Srivastava, Vivek Ashok Bohara, Anand Srivastava, and Martin Maier, “Traffic Prediction Assisted Wavelength Allocation in Vehicle-to-Infrastructure Communication: A Fiber-Wireless Network Based Framework,” in *Vehicular Communications*, vol. 45, 2024, doi: 10.1016/j.vehcom.2023.100713.

1.2.5 Priority Based V2V Data Offloading Scheme for FiWi Based Vehicular Network Using Reinforcement Learning

Intelligent vehicular network is one of the popular paradigms for 6G networks. With the growth in vehicular traffic density, it is essential to ensure safety and security by providing ultra reliable low latency (URLL) services for vehicular communication. Moreover, along with the URLL services, it is also essential that these services are energy-efficient. These requirements can be fulfilled by the utilization of FiWi networks. In this work, we consider a FiWi-based vehicular network that consists of an optical fiber back-end network with a wireless V2I network at the front end. Specifically, to ensure that high-priority vehicular traffic has lower latency and energy consumption, we propose a reinforcement learning (RL) based DDQN scheme that chooses the cluster head for vehicular communication. The proposed algorithm uses energy and latency-aware cluster-head selection that meets the intelligent transport systems (ITS) requirements. The proposed algorithm is compared with the non-RL-based approach, such as random and max-queue-based cluster-head selection in terms of energy, latency, throughput, and reliability. This work resulted in the following publications:

7. Akshita Gupta, Saurabh Jaiswal, Vivek Ashok Bohara and Anand Srivastava, “Pri-

ority Based V2V Data Offloading Scheme for FiWi based Vehicular Network using Reinforcement Learning,” in *Vehicular Communications*, vol. 42, 2023, ISSN 2214-2096, doi: 10.1016/j.vehcom.2023.100629.

8. Akshita Gupta, Abhishek Pratap Singh, Arunima Srivastava, Vivek Ashok Bohara, Anand Srivastava, and Martin Maier, “Machine learning based V2I and V2V Data Offloading for FiWi based Vehicular Communication,” submitted to *IEEE Transactions Intelligent Transportation Systems (T-ITS)*.

1.2.6 Emergency Path Planning for Safe-Driving in TransVerse Enabled Connected Vehicular Network

The future intelligent transportation systems promise to improve traffic safety and security along with reducing the driver’s workload. In this work, we consider a pre-emptive emergency situation, wherein we design a safe-driving maneuver problem for TransVerse to compensate for driver reaction latency. The proposed scheme balances the risk of collision and the spectral and computation resources required by the network. This combination of the spectral and computation resources required is also known as the utility of the vehicular network. Further, an emergency maneuver is proposed to suggest a lane-changing maneuver based on the safe link quality index for vehicles in the vicinity of the emergency vehicle, also known as collision risk vehicles (CRVs). Moreover, based on the current position of the vehicles and the proposed safe maneuver, we propose a driving mode advisory to the drivers to provide a speed profile and real-time high-level driving modes advice on acceleration, cruise, and engine brake. We evaluate the performance of the proposed safe maneuver planning for CRVs in terms of collision probability, velocity, driving mode, and end-to-end lane-changing latency. The publications based on the above work are:

9. Akshita Gupta, Anand Srivastava, Vivek Ashok Bohara, and Martin Maier, “Driv-

ing Mode Advisory for Emergency Maneuvering in TransVerse Enabled Connected Vehicular Network,” accepted to IEEE Transactions on Systems, Man, and Cybernetics: Systems.

10. Akshita Gupta, Vivek Ashok Bohara, Anand Srivastava, “Digital Twin for Connected Vehicular Network: A Road Towards Sustainable Future,” accepted to IEEE Systems, Man, and Cybernetics Magazine.

1.3 Other Contributions

The other works that are not discussed in this thesis but are authored by the author of this thesis are mentioned below:

11. Akshita Gupta, Saurabh Jaiswal, Martin Maier, Vivek Ashok Bohara, Anand Srivastava, “Digital-Twin Enabled Time Ahead Resource Allocation for Integrated Fiber-Wireless Connected Vehicular Network,” accepted to IEEE Journal of Communications and Information Network, Sept. 2024.
12. Priyanka Singh, Akshita Gupta, Vivek Ashok Bohara and Anand Srivastava, “QoS-Aware Reliable Architecture for Broadband Fiber-Wireless Access Networks,” in IEEE Systems Journal, doi: 10.1109/JSYST.2022.3149854.
13. Akshita Gupta, Anant Agarwal, and Vivek Ashok Bohara, “Adaptive Traffic Signal Cycle Control for Green City Traffic Management,” accepted to 2024 IEEE TENCON, December 1-4, 2024, in Marina Bay Sands, Singapore.
14. Hanshita Prabhakar, Saumya Chaturvedi Chaturvedi, Akshita Gupta, and Vivek Ashok Bohara, “Performance Analysis of THz and VLC Systems Under the Impact of Weather and Human Blockages,” accepted to 2024 IEEE TENCON, December 1-4, 2024, in Marina Bay Sands, Singapore.

15. Akshita Gupta, Drishti Diwani, Vivek Ashok Bohara, and Anand Srivastava, "QoS Aware Task Offloading for Digital-Twin Enabled Connected Vehicular Network," 2024 IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 2024, pp. 1-6, doi: 10.1109/WCNC57260.2024.10570972.
16. Priyanka Singh, Akshita Gupta, Vivek Ashok Bohara and Anand Srivastava, "Cost Effective Hybrid FSO-Wireless Architecture for Broadband Access Network," 2022 International Conference on Optical Network Design and Modeling (ONDM), 2022, pp. 1-6, doi: 10.23919/ONDM54585.2022.9782861.
17. Mehreen, Akshita Gupta, Vivek Ashok Bohara and Anand Srivastava, "A Hybrid Wavelength Allocation Framework for Fiber-Wireless Based Vehicle-to-Infrastructure Communication Network," 2022 IEEE 95th Vehicular Technology Conference: (VTC2022-Spring), Helsinki, Finland, 2022, pp. 1-7, doi: 10.1109/VTC2022Spring54318.2022.9860993.
18. Neetu R. R., Akshita Gupta, G. Ghatak, Anand Srivastava and Vivek Ashok Bohara, "Joint Bandwidth and Position Optimization in UAV Networks Deployed for Disaster Scenarios," 2021 National Conference on Communications (NCC), Kanpur, India, 2021, pp. 1-6, doi: 10.1109/NCC52529.2021.9530185.
19. Kinshu Kumar, Akshita Gupta, Vivek Ashok Bohara and Anand Srivastava, "Centralized vs Decentralized Resource Analysis of Green FiWi Networks," 2021 IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), Hyderabad, India, 2021, pp. 90-95, doi: 10.1109/ANTS52808.2021.9937014.

Chapter 2

Literature Review and Motivation

In this chapter, we discuss the existing literature and motivation for the works presented in the thesis. The work is primarily subdivided into four broad areas as follows.

2.1 Energy Resource Allocation in Green FiWi Network

2.1.1 Literature Review

The exponential growth in the number of devices as well as ever-increasing bandwidth requirements, has led to a considerable increase in the energy requirements of access networks. The energy conservation mechanisms in the existing literature usually focused on the sleeping modes of the network components to save energy, for e.g., in ITU-T G.987.3 [1], cyclic sleep and doze modes are proposed to reduce ONU power consumption for G-PON. For FiWi network, researchers have tried to reduce energy consumption at both optical and wireless ends. The fixed limitations of grid power, such as intermittency and large carbon dioxide (CO_2) emissions, have motivated the researchers to explore alternate sources of energy that are green and renewable. The addition of renewable energy sources will enhance the energy conservation of the network along with the reduction in carbon footprint. For instance, in [18], [19], the authors presented solar-powered base stations (BSs) for off-grid and on-grid scenarios, respectively. In [18], the authors proposed a temporal energy allocation algorithm to allocate hourly energy to the BSs, while

in [19] the authors used load proportion to allocate energy to the BSs. Once the energy is allocated to the BS, the trade-off between latency and energy consumption is analyzed. The authors in [20] exploited the advantages of the anti-correlated energy harvesters to use renewable energy sources more efficiently. By deploying anti-correlated energy harvesters, the surplus power from one BS can be transferred to deficit BS. Further, the results demonstrated that with the optimization scheme, an energy conservation of up to 40% can be achieved. An optimal sizing scheme for battery, PV panel, and wind-powered off-grid telecom BSs is proposed in [21]. The authors used the grey-wolf optimization method to formulate a multi-objective problem that includes the leveraged cost of electricity, excess energy, and loss of power-supply probability. The authors were able to show that with the proposed approach, they were able to get a Pareto optimal solution to the problem. However, to the best of our knowledge, a joint optimization framework to optimize the energy resource allocation at both the wireless and optical ends of the FiWi network has not been investigated yet.

2.1.1.1 Renewable Sources of Energy For Green Networks

In addition to energy-saving, renewable energy sources also have a socio-economic impact. The economic impact of renewable energy sources such as solar power and wind turbines installed with a battery storage system is studied in [22] for a residential micro-grid. In [23], the authors presented the total cost analysis for distributed and centralized energy resources for the co-planning framework. The authors considered wind turbines, PV panels, and energy storage systems to analyze the total cost of the transmission system. In [24], the environmental impact of the utility grid and different sources of energy, such as solar energy and battery storage systems for Colorado, in terms of greenhouse gas or CO₂ emissions, has been studied. Further, the authors also proposed energy efficiency benchmarks from both system-wide and user-side perspectives. However, the authors modified the standard energy consumption protocol to conserve the energy and

did not use any renewable sources of energy to operate the network components. In [25], the authors used a combination of renewable energy sources such as solar as well as other non-renewable sources such as batteries for FiWi network. Specifically, an energy resource allocation approach to operate ONU is proposed for on-grid as well as off-grid scenarios¹. However, they did not use any ML based energy resource allocation to allocate the energy resources dynamically based on the availability of solar power. In [26], the authors formulated a two-stage photovoltaic (PV) planning framework for distribution grids using a game theory approach. First, the authors computed the optimal installation capacity of PV panels, then they proposed a model to optimally allocate PV panels among the solar producers and consumers to minimize the active power flow in the system. However, the authors did not use any other renewable source such as wind, nor did they employ any ML based technique for allocating the PV panels. The authors in [27] used a cooperative game theory scheme to investigate the performance of shared PV panel system among community of households. In [28], a power allocation scheme for battery cluster switching is proposed to alleviate overcharging and deep-charging of batteries as well as to minimize the battery power loss. However, the authors did not consider solar and wind energy. The authors in [29] developed a novel statistical model of the harvested energy from renewable energy sources considering harvest-store-consume (HSC) architecture. They derived the closed-form expressions for the density functions and moments of the harvested solar and wind power using clouds occlusion, wind speed, etc. Further, in [30], the authors reviewed the performance of miniaturized wind energy harvesters (MWEHs). A miniature wind energy harvester design which works at low wind speed with a wide operational wind speed range can significantly improve the operation cycle of many systems and can result in more robust Internet of Things (IoT) applications. However, in order to capture the day-to-day fluctuation in wind and solar power, the practical values for parameters such as cloud occlusion are required. Moreover, unlike solar power, the wind power do not follow

¹The scenarios where grid energy is utilized to power the network components are called on-grid scenario, whereas the scenarios where grid energy is not utilized are called off-grid scenarios.

any specific hourly pattern. Thus, it is difficult to consider any specific statistical model for wind power. Table 2.1 summarizes the related works in energy resource allocation for green communication networks.

2.1.1.2 Forecasting The Availability of Solar Power

The accurate predictions about the availability of the green sources of energy will facilitate to quantify their future availability. In [33], the authors proposed the Markov Chain model to forecast the hourly day-ahead solar irradiance for Jodhpur, India. The authors achieved a maximum solar irradiance root mean square error (RMSE) of 2200.818 W/m² for October 2014 and maximum mean absolute error (MAE) of 90.985 W/m² for July 2014. A typical Markov chain model to quantify the solar prediction for bi-hourly data is proposed in [34]. The performance in terms of mean square error (MSE), MAE, RMSE, standard deviation error (SDE) is compared with four types of prediction model, namely, persistent, autoregressive, Gaussian process regression (GPR) model, and neural network (NN) [34]. The results demonstrated that using Markov switching, the authors were able to get the best performance, followed by NN, whereas the performance of GPR is the worst. Using artificial NN (ANN), the authors in [35] compared the performance of hourly solar power forecasting with multiple layer regression and persistence method. The authors showed that depending on the weather conditions, the forecast might vary. For instance, clear sky hours have better forecast compared to cloudy hours. The authors in [36] proposed a model composed of knowledge based NN (KBNN) and multilayer perceptron (MLP) for forecasting solar power. The results demonstrated that the model is reliable even when the training data is insufficient. Moreover, the model is shown to have an accuracy improvement of 65.4% compared to existing methods. In [37], the authors used long short-term memory (LSTM) model for solar energy prediction for Korea. The authors used weather forecast statistics such as temperature, sky cover, humidity, etc., to forecast solar irradiance. Moreover, they showed that the LSTM model had the RMSE coefficient

Table 2.1: Summary of Related Works on Green Communication Networks

Reference	Contributions	Remarks
[25]	Proposed energy resource allocation scheme for FiWi network	No joint energy resource allocation and no use of wind energy
[6]	Proposed AFALT scheme to minimize the energy consumption for IoT over FiWi network	No renewable energy.
[31]	Proposed ECO-FiWi scheme to conserve energy for FiWi network that schedules power saving modes of ONU, AP, and users	No renewable energy.
[32]	Exploited the different modes of operation for ONUs and APs to conserve energy in FiWi network	No renewable energy.
[18]	Proposed a temporal energy allocation algorithm to allocate hourly energy to the BSs	Use solar energy along with batteries for cellular network. No analysis for FiWi network and no use of wind power.
[19]	Used load proportion to allocate energy to the on-grid BSs	Use solar energy along with batteries for cellular network. No analysis for off-grid FiWi network and no use of wind power.
[20]	Exploited the advantages of the anti-correlated energy harvesters to power BSs	Focus on resource allocation before planning the network architecture
[21]	Proposed an optimal sizing scheme for battery, PV panel, and wind-powered off-grid telecom BSs	Includes analysis for cellular network on leveraged cost of electricity, excess energy, and loss of power supply probability. No analysis for FiWi network
[22]	Studied socio-economic impact of solar energy, wind energy and batteries on residential microgrid	No joint resource allocation for FiWi network
[23]	Analysed the total cost analysis for a co-planning framework for distributed and centralized resources	No joint resource allocation for FiWi network and no social impact analysis
[24]	Analysed the CO ₂ emissions for Colorado from utility grid, solar and battery powered stations	No joint resource allocation for FiWi network or cost analysis

of 12%. Table 2.2 summarizes the related works on solar power predictions.

Table 2.2: Summary of related works on solar prediction

Reference	Algorithm used	Contributions
[33]	Markov Chain model	Forecasted solar irradiance by investigating the use of the Markov chain model for a short-term period
[34]	Markov switching model	Markov regime switching model performs better than solar radiance forecasting models, such as the persistence model, neural network, GPR, and auto regression model
[35]	Artificial NN	Artificial NN model to produce solar power forecasts compared to linear regression and persistence models
[36]	Combination of KBNM and MLP	Proposed model had a 64.5% more accuracy compared to existing models
[37]	Long Short-Term Memory	Used local weather forecast and a pre-trained LSTM model to predict next-day solar irradiance

2.1.2 Motivation

As evident from above, the researchers have explored the different sleeping modes of ONU and AP for green communication networks. However, the recent focus on green sources and energy and erratic grid power supply motivates us to explore the use of renewable sources of energy instead of traditional methods. This section of the thesis focuses on the use of solar and wind power, which has been well-studied for cellular networks, especially where the BSs are equipped with renewable sources of energy. However, to the best of our knowledge, the use of solar and wind to power the FiWi network has not been investigated yet. Further, along with the focus on renewable sources of energy, it becomes essential to consider the user requirements and the availability of renewable energy at different locations. Thus, this section focuses on allocating the energy resources to the network by taking into consideration the throughput profile of the users and renewable energy availability constraints. Moreover, to reduce the impact of the availability of renewable

sources of energy, we also propose an ML-based energy resource allocation scheme in Chapter 4 that predicts the solar power available to the network. This prediction will help the network to utilize energy resources based on the availability of renewable energy each day.

2.2 QoS Analysis for High Throughput FiWi Network

2.2.1 Literature Review

The convergence of optical and wireless technologies can be used to realize FiWi architecture systems. This architecture has gained a lot of attention for supporting a large number of potential subscribers with universal access to information and advanced services in a cost-efficient manner [38]. By utilizing next-generation WLANs, such as IEEE 802.11n and 802.11ac and 10-Gigabit-capable passive optical networks (XG-PON), we aim to achieve high-quality broadband connectivity to provide critical information related to education, health services, agriculture, e-government, etc. to the citizens in rural areas at low cost. WiFi-based WLANs operate on unlicensed bands, possess broadband capabilities, and are easy to deploy, which makes them a much more cost-effective choice compared to broadband cellular networks. In order to provide QoS differentiation, IEEE 802.11e was introduced that defines two mechanisms, enhanced distributed channel access (EDCA) and hybrid coordination function (HCF) controlled channel access (HCCA), both backward compatible with the legacy distributed coordination function (DCF) access mechanism to provide QoS support at media access control (MAC) layer for different kinds of applications in WLANs. IEEE 802.11e EDCA standard specifies four access categories (ACs): voice, video, BE, and background. To impart service differentiation among wireless stations, each AC employs a specific parameter set that includes: (a) Minimum

contention window ($CW_{\min}$), (b) Maximum contention window ($CW_{\max}$), (c) Arbitration inter-frame spacing (AIFS) and (d) Transmission opportunity ($TXOP$). Based on the values assigned to these parameters, the ACs' performance can be altered.

Applications such as video-on-demand and content-driven applications generate the major portion of upstream traffic besides storage applications. In Latin America, too, file sharing and web browsing account for the majority of upstream traffic, while real-time entertainment services account for 20% (approx.) traffic in the upstream direction. This indicates that the applications, such as file sharing and web browsing, control a major amount of upstream traffic across the globe [[39], [40], [41], [42]]. In urban scenarios, real-time entertainment with video streaming will outpace the data consumption; however, in rural scenarios, the traffic is still dominated by low data rate services. From these global survey reports, it is evident that BE traffic constitutes the major portion of the upstream traffic worldwide, as shown in Table 2.3, and there is a need to provide sufficient bandwidth to BE service while keeping the delay and PLR of real-time voice and video services within the ITU-T Standardized tolerable limits [43].

Table 2.3: Upstream global IP traffic distribution

Regions	Voice (%)	Video (%)	BE (%)
Asia Pacific	5	31	64
Africa	10	17	73
North America	8	22	70
Latin America	12	20	68

There is a plethora of literature that focused on architecture design and guaranteed QoS of stand-alone architectures. In [44], authors discussed the impact of AIFS and contention window (CW) differentiation in the EDCA network's performance and the problems related to the co-existence between 802.11e contention-based stations with legacy 802.11 stations. However, besides these parameters, the impact of $TXOP$ on the performance of the EDCA network also needs to be considered. In [45], the IEEE 802.11e EDCA network with AIFS and back-off window differentiation was considered, and it

concluded that back-off window differentiation is more suitable due to its lesser tuning parameters and more exactness. However, [45] did not consider how *TXOP* can affect the performance of the network. In [46], the authors introduced an advancement of EDCA scheme for dense IEEE 802.11 ax schemes. The authors extended the EDCA queues from 4 to 7 to assign the priority levels to different kinds of video traffic (high definition (HD), 4K/8K videos), but the paper did not consider the impact of tuning the network parameters. Though there are several DBA strategies for stand-alone XG-PON, very few are designed for integrated architecture with XG-PON as back-haul. 10-Gigabit PON access network (X-GIANT) DBA was designed in [47] for standard-complaint XG-PON in NS-3, and it was demonstrated that in terms of latency and throughput, XG-PON requirements are satisfied for a wide range of offered load. In [48], a deficit algorithm was introduced that provides required X-GIANT prioritization and fairness among three aggregated application types in LTE backhaul. These aforementioned studies either focus on the performance of DBA in stand-alone XG-PON or consider XG-PON with LTE as a front-haul network. In [49], the authors implemented integrated XG-PON and EDCA-based WiFi network by considering the QoS mapping as given in [50] with different packet sizes and data rates and utilized the efficiency of deficit DBA in improving the fairness of network by provisioning enough bandwidth for BE services.

2.2.2 Motivation

As we know, one of the key advantages of utilizing optical networks is the high bandwidth of optical fiber capability. However, this bandwidth needs to be efficiently allocated to the users depending on the type of traffic generated by each user. Though there are several dynamic bandwidth allocation (DBA) strategies for stand-alone XG-PON, but very few are designed for integrated architecture with XG-PON as back-haul. 10-Gigabit PON Access network (X-GIANT) DBA was designed in [47] for standard-complaint XG-PON in network simulator 3 (NS-3), and it was demonstrated that in terms of delay and through-

put, XG-PON requirements are satisfied for a wide range of offered load. The authors in [51] introduced an efficient bandwidth utilization (EBU) DBA that forwards unused upstream transmission opportunity from one T-CONT to another T-CONT of a single type. Improvement in mean delay performance for T-CONTs 2 and 3 was demonstrated, whereas there was a decline in the mean delay performance for T-CONT 4, which handles BE traffic. In [52], a deficit algorithm was introduced that provides required X-GIANT prioritization and fairness among three aggregated application types in LTE backhaul. These aforementioned studies either focus on the performance of DBA in stand-alone XG-PON or consider XG-PON with LTE as a front-haul network. In [49], the authors implemented integrated XG-PON and EDCA-based WiFi network by considering the QoS mapping as given in [53] with different packet sizes, data rates and utilized the efficiency of deficit DBA in improving the fairness of network by provisioning enough bandwidth for all data traffic services.

2.3 Latency Reduction in FiWi Based Vehicular Network

2.3.1 Literature Review

The advent of the Internet of vehicles has facilitated new modes of vehicular communication such as V2V and V2I [54]. V2I communication connects several vehicles with road side units (RSUs) to help manage and supervise the traffic in an efficient manner. Significant literature has been devoted to providing reliable and low-latency services through V2I communication. However, one of the key challenges in V2I communication is fast and secure handovers when the vehicle is commuting between the RSUs. For high density and high mobility scenarios, the authors in [55] proposed an extension of the trustful space-time protocol (TSTP) which is capable of performing handovers among roadside gateways

with low roaming latency of about 14 millisecond (msec). In [56], the performance of a low latency V2I system was enhanced by using cooperative relay V2V communication. The data transmission between a distant vehicle and the base station was done by relaying data to the nearest vehicle. This enhanced throughput for the distant vehicle also helped in avoiding re-transmissions. The authors in [54] used such a model for FiWi based V2I communication for task offloading in vehicular edge collaborative network (VECN). They exploit the high capacity and low latency characteristics of an optical network along with the flexibility and mobility of the wireless network [54]. The authors in [54] showed that the SDN based load-balancing scheme can achieve improved performance in terms of processing latency by employing the edge servers' computation resources more efficiently. In [57], the authors configured users into logical PONs on demand. Traffic is planned in the time domain, allowing PON branches to share wavelength resources without the need for quick wavelength tuning. When logical PONs cannot provide enough bandwidth for users, they were changed to enable more effectively shared and reassigned wavelengths. [58] presented the requisite level of wavelength and timeslot sharing while demonstrating wavelength reallocation of optical network units (ONUs) on demand, further emphasizing reconfigurability while boosting network flexibility without increasing complexity and expense. Focusing on the algorithms, in [59], the authors observed that the introduction of multi-threaded MAC algorithms to achieve dynamic bandwidth and wavelength assignment improved the performance of a long-reach wavelength-division multiplexing/time-division multiplexing (WDM/TDM) PON. The authors in [60] asserted that mixed integer linear programming can be used to accomplish this. [61] suggested a time and wavelength multiplexing (TWDM) multi-PON can be programmed to reschedule wavelength allocation by relying on wavelengths shared by all connected TWDM-PON branches in order to reduce power consumption and deployment costs. For NG-PON2, the authors of [62] created a dynamic wavelength and bandwidth allocation method to ensure consistency in processing among different classes of service across all

ONUs in agreement with their QoS requirements.

Nowadays, ML based frameworks are increasingly playing an important role in enhancing the performance of vehicular networks. The parameters can be learned from the environment, which can aid improve the services of a vehicular network. In [63], a traffic-flow model for Yanan east road tunnel is presented. The authors used an adaptive neuro-fuzzy inference system for short-term traffic prediction. It was inferred that the traffic flow for the same lane was correlated; however, traffic flow and vehicle speed were found to be uncorrelated. The authors in [64] used the auto-regressive model to estimate up to 30-min ahead real-time traffic flow for each link. The model was used to estimate various factors that affected the traffic flow, such as accidents, road closures, public events, etc. It was observed that the estimation error for a short duration of time such as 5 min was 5%; however, it increases with the duration of estimation. For instance, the prediction for a 30 min duration had an estimation error of 12%. In [65], an intelligent internet-of-vehicles (IoV) network is presented where authors used deep learning for urban road network traffic flow prediction. This information is utilized by traveling vehicles to analyze road traffic conditions. The authors used long-short term memory (LSTM) and sparse auto-encoder to predict the traffic flow of the vehicular network. Thus, traffic flow prediction can help build an intelligent transportation system by reducing road risk by predicting road traffic conditions, prompting a quick emergency response, reducing road accidents, etc. Table 2.4 summarizes the existing works in vehicular networks.

2.3.2 Motivation

The vehicular network poses critical safety and security challenges to the communication networks. Ensuring that the QoS requirement is met for vehicular data traffic is a critical challenge in vehicular networks. As evident from the above works, several works have utilized edge-based data offloading schemes in communication networks. However, to the best of our knowledge, no work has explored the use of edge-based networks for

Table 2.4: Comparison of Existing Works on Vehicular Network

Ref	Data of-fload-ing	Learning (ML/RL)	Priority of traffic	Back-end fiber net-work	Performance Metrics			
					Energy	Latency	Throughput	Reliability
[66]	✓	RL	✓	✗	✓	✓	✗	✗
[67]	✓	ML	✗	✗	✓	✓	✗	✗
[68]	✓	ML	✗	✗	✗	✓	✗	✗
[69]	✓	RL	✓	✗	✗	✓	✗	✗
[70]	✓	RL	✗	✗	✗	✓	✗	✗
[71]	✓	✗	✓	✗	✗	✓	✗	✗
[72]	✓	✗	✗	✗	✗	✓	✗	✗
[73]	✓	RL	✗	✗	✗	✓	✗	✗
[74]	✓	ML	✗	✗	✗	✓	✗	✗

the different applications of vehicular data traffic. Moreover, data offloading in FiWi-based vehicular networks that utilize data traffic classification in vehicular networks has not been explored yet. Thus, we propose a wavelength allocation algorithm to reduce the wavelength switching in FiWi-based V2I network that utilizes vehicular data traffic classification for data offloading. Furthermore, we also explore V2V data offloading along with V2I offloading for the critical vehicular data traffic application.

2.4 Emergency Path Planning for Safe-Driving in Trans-Verse

2.4.1 Literature Review

In this section, we discuss the related works on Metaverse-based connected vehicular network and self-driving vehicles.

2.4.1.1 Metaverse-based Connected Vehicular Network

Increasing traffic congestion and the associated environmental problems have long been an obstacle to healthy urban development. In recent past, ITS has emerged as an effective means to meet this challenge. ITS have been widely adopted to keep the vehicular network safe, secure, comfortable, and economical. Inline with the goals of ITS, recent literature have introduced the terms TransVerse, Metaverse, or the federation of Metaverses for ITS [75], [76]. The authors of [75] investigated a management architecture based on distributed autonomous organizations (DAOs) that considers both the technical and societal aspects of TransVerse. The authors in [75] utilized blockchain to guarantee a secure exchange of information between physical space and their digital counterparts and ultimately conceptualize the Internet of Minds (IoM). For federated intelligence and parallel learning in TransVerse the authors in [76] presented a transportation foundation model. The presented model enabled DAOs with various federated technologies and distributed operations from federated control, federated services, federated management, and federated security to federated ecology for transportation intelligence in smart cities. From the perspective of the cyber-physical-social system (CPSS), [77] proposed an intelligent cockpit composition framework that includes three layers of interaction, perception, and cognition. The framework can dynamically perceive human intelligence and provide feedback, which is beneficial to provide an efficient, safe, secure, and enjoyable experience to improve road traffic safety. The authors of [78] proposed a hierarchical game-theoretic Coded distributed computing (CDC) framework for the Metaverse services, especially for the vehicular Metaverse. CDC introduced computing redundancy to the Metaverse by utilizing coding techniques, and the Metaverse service providers (MSPs) only need to collect the computing results of rendering tasks from a subset of workers. Thus, CDC significantly reduces the computation latency and improve the data processing reliability and consequently alleviate the straggler effects. In order to resolve the spatiotemporal conflicts among the connected and autonomous vehicles (CAVs), a lane-free trajectory

planning strategy is proposed in [79], wherein trajectories are developed for self-driving vehicles to effectively share the limited space at the road intersections.

2.4.1.2 Self-Driving Vehicles and Driver’s Reaction Time

Some of the critical indicators of dangerous situations on the road while driving can be speed, orientation of the vehicles, and traffic density of the vehicles. Therefore, there is a need for a maneuvering mechanism that handles the vehicles approaching towards an emergency zone (e.g., road hazard and road accident spot). Moreover, for self-driving vehicles, on-road safety and reliability could be ensured by designing an optimal driving maneuver during emergencies. The authors of [80] presented a context-aware navigation protocol (CNP) that enhanced the safety of vehicles driven on urban roads. The authors realized a highly interactive traffic scenario for self-driving or semi-automatic vehicles in vehicular cyber-physical systems (CPS). The authors of [81] proposed a connected vehicle adaptive cruise control (ACC) strategy that utilized vehicle motion and driving behaviors to identify the motion patterns, such as constant speed, acceleration, and deceleration. The proposed strategy is utilized to ensure a minimum safety headway and harmonious speed change of the vehicle in accordance with the preceding vehicle. With the proposed scheme, the authors were able to reduce the response time of CV-ACC by 0.5s compared to the traditional ACC. The authors of [82] demonstrated field tests with 17 participants for CAVs. The authors utilized various physiological, demographical, and vehicle trajectory data to characterize distracted driving by quantifying the response time and intensity to an emergency stop using the driver’s physiological states. The authors of [83] modeled a driver’s emergency braking responses and applied a framework of human perception, behavior, and cognition based on the predictive processing theory. The authors of [84] proposed an eco-driving assistance system (EDAS) to design an optimal control problem to provide drivers with driving mode advice. The authors focused on minimizing the drivers’ reaction latency by following the driving mode advice. This not

only mitigates the driver’s reaction latency but also impacts the fuel savings. Further, the authors of [85] proposed an adaptive optimal control design method that considers human–vehicle interaction and heterogeneous driver behavior for a platoon mixed with multiple preceding human-driven vehicles. The proposed method allows the CAV controller to adapt to different platoon dynamics caused by unknown and heterogeneous driver-dependent parameters. To enhance the stability and safety of the traffic flow, the authors of [86] designed a robust feedback controller that utilized the current states of each vehicle to overcome the influence of uncertain human driving reaction time.

Table 2.5: Comparison of Related Works on MetaVerse Enabled Path Planning

Ref.	Metaverse	Prob. of collision	Emergency Manueuer Planning	Driving Mode	Driving Velocity	Driver’s Reac- tion Time	End-to- end Latency
[75]	✓	✗	✗	✗	✗	✗	✗
[76]	✓	✗	✗	✗	✗	✗	✗
[80]	✗	✓	✓	✗	✓	✗	✗
[81]	✗	✗	✗	✗	✓	✗	✗
[82]	✗	✗	✗	✗	✓	✓	✗
[83]	✗	✗	✗	✗	✗	✗	✗
[87]	✗	✗	✗	✗	✗	✗	✗
[86]	✗	✗	✗	✓	✓	✓	✗
[85]	✗	✗	✗	✗	✓	✓	✗
Proposed	✓	✓	✓	✓	✓	✓	✓

2.4.2 Motivation

As evident from the above works, the Metaverse has recently been utilized for various applications such as virtual city development, education, and digitalization of the economy etc. For instance, the authors of [88] proposed a virtual city development framework for the Metaverse. The proposed virtual city utilized a collaborative edge-driven scheme for computation, sensing, communication, and storage of resources at the network edge to achieve the desirable qualities and features of the Metaverse. Specifically, the au-

thors proposed three frameworks for virtual city development: i) a physical-virtual world synchronization, ii) edge rendering services among resource-constrained users, and iii) a physical-virtual world optimal resource allocation. Moreover, in the above works, the Metaverse is generally utilized to enhance learning among vehicles or to ensure security and provide regular services to vehicular users in CAVs. However, to the best of our knowledge, the benefits and usage of the Metaverse for self-driven vehicles, especially in emergency scenarios, have not yet been explored. Specifically, during emergency situations, which can cause high traffic congestion, leading to reduced driving comfort and high travel time, it becomes essential to ensure safe maneuvering. This part of the thesis paves the way for future 6G applications by exploring the utilization of Metaverse for vehicular networks.

2.5 Organization

The rest of the report is organized as follows. Chapters 3 and 4 are focused on the first section of the thesis on resource allocation in green FiWi networks. Chapter 3 presents our work on energy resource allocation for green FiWi networks to provide a 24×7 connectivity to the users. An extension of energy resource allocation for green FiWi network based on ensemble learning is presented in Chapter 4. In Chapter 5, we focus on the second section of the thesis on QoS analysis for high throughput FiWi networks. We prioritize the FiWi network traffic based on the KPI requirements and allocate the network resources based on the priority of the traffic. This work was extended for vehicular network traffic in Chapters 6 and 7, where we minimized the latency of FiWi network traffic based on the priority of the vehicular data traffic, as mentioned in the third section of the thesis. In Chapter 8, we focus on the fourth section of the thesis and utilize the Transportation Metaverse-based digital twin for emergency path planning for FiWi-based connected vehicular network. Finally, Chapter 8 concludes the work presented in this

report and highlights the possible future research directions.

Part I

Energy Resource Allocation for Green FiWi Networks

Chapter 3

Energy Resource Allocation in Green FiWi Network

3.1 Introduction

The advantages of renewable sources of energy, such as hydroelectric, geothermal, solar, wind, etc., do not only help in reducing the carbon footprint but also promote sustainable development. As per the insights shared in [89], only 13% of the total energy served globally was supplied by renewable sources of energy. Further, out of the total renewable energy, only 32% of the energy is served using solar power. However, due to ease of availability, solar and wind power have a higher potential to serve as an alternative to non-renewable sources of energy. There is a growing impetus to provide broadband coverage to both urban and rural environments, this may lead to a significant increase in energy consumption. The problem will be further compounded due to the limited availability of grid power supply and power outages, especially in rural areas. Therefore, it is necessary to take renewable sources of energy into account, especially when the grid power supply is not available. This chapter proposes a resource allocation scheme to power FiWi network components such as collocated ONU-access point (AP) to maintain the QoS of the end-users in a solar and wind-powered FiWi network.

3.2 Contributions

The renewable sources of energy are generally intermittent and may not be available to power the network components throughout the day. This increases the dependency of the FiWi network components on the battery power supply [90], [91]. Thus, energy resource allocation framework is required to allocate the energy resources based on the throughput and solar/wind power availability at the location. The co-located ONU and AP device called ONU-AP [31], [92] is powered using lead-acid batteries along with solar and/or wind energy. This work analyses the energy resource allocation framework for four different cases where ONU-APs are powered by the following sources: a) Case I: batteries with fixed PV panels, b) Case II: batteries with rotational PV panels, c) Case III: batteries with fixed PV panels and wind turbine, and d) Case IV: batteries with rotational PV panels and wind turbine. Further, in order to study the impact of network load on energy resource allocation, users are considered to have three kinds of average throughput requirements. Moreover, an analytical framework is derived to validate the accuracy of the proposed approach. In order to analyze the socio-economic impact of the energy resource allocation framework, the work presents the economic and social impact in terms of cost and CO₂ emissions at different locations and the throughput requirement.

3.3 System Model

Fig. 3.1 shows the system architecture for the considered FiWi network. The XG-PON is connected to a WiFi module. The XG-PON consists of an optical line terminal (OLT) at the central office connected to ONUs using an optical distribution network (ODN) and passive optical splitter. The XG-PON uses time division multiple access (TDMA) for upstream traffic flow, and for downstream traffic flow, time-division multiplexing (TDM) is used [2]. In the considered FiWi architecture, each ONU is connected to a WiFi AP

using a point-to-point ethernet link. user equipments (UEs) are connected to AP via wireless links. The renewable energy sources are installed at ONU-AP. Precisely, it is assumed that ONU-AP is powered by different energy sources such as, PV panels, wind turbines and batteries, as shown in Fig. 3.2.

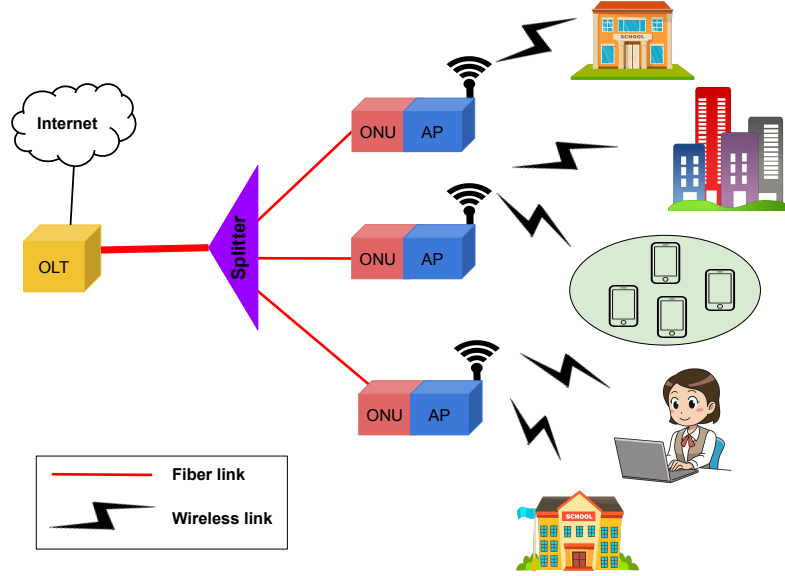


Figure 3.1: FiWi network architecture

3.3.0.1 Throughput And traffic model

The density of the users connected to the network depends on the time of the day. For the peak traffic hours, the density of the users is higher than that of the other hours. According to [93], the throughput profile for the users follows an exponential pdf given as:

$$f(y_e) = r_g e^{(-r_g y_e)}, y_e \geq 0, \quad (3.1)$$

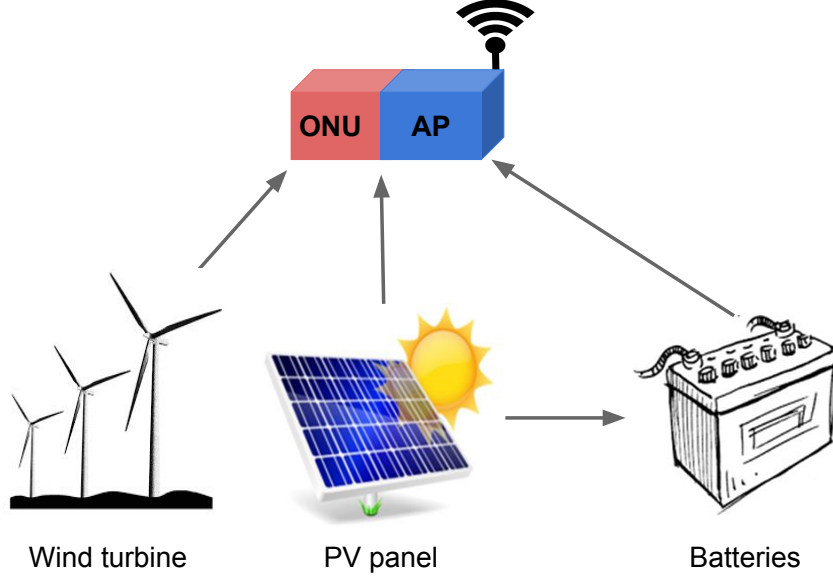


Figure 3.2: System model to power ONU-AP.

where, y_e is the exponentially distributed random variable, r_g is the rate parameter given by gaussian mixture model (GMM) and is a function of time of the day t as [93]:

$$r_g = \sum_{i=1}^{N_p} a_i e^{\left(-\left(\frac{t-L_i}{W_i}\right)^2\right)}, \quad (3.2)$$

where, a_i is the amplitude of the i^{th} peak, L_i is the location of the centroid of the i^{th} peak, W_i relates to the peak width of the i^{th} peak, t is the time (in hours) of the day, and $N_p = 7$ represents the number of peaks in the data series [93]. The values of $\mathbf{a} = [3.263 \times 10^6, 0.0781, 0.6616, 0.1097, 0.2584, 0.1822, 0.1652]$, $\mathbf{L} = [75.273, 3.85, 4.971, 2.996, 1.868, 3.221, -2.871]$, and $\mathbf{W} = [12.56, 0.4829, 1.77, 0.862, 1.543, 5.972, 84]$ [93].

Fig. 3.3 shows the three categories of aggregate throughput profile of all the users connected to the AP. It is evident that with the increase in average throughput value from 20 to 60 Mbps, the hourly throughput increases. Further, for the peak traffic hours (17:00-19:00 hrs), the number of users in the network increases, and therefore, a peak in throughput profile can be observed. Moreover, in the night (3:00-7:00 hrs), when the

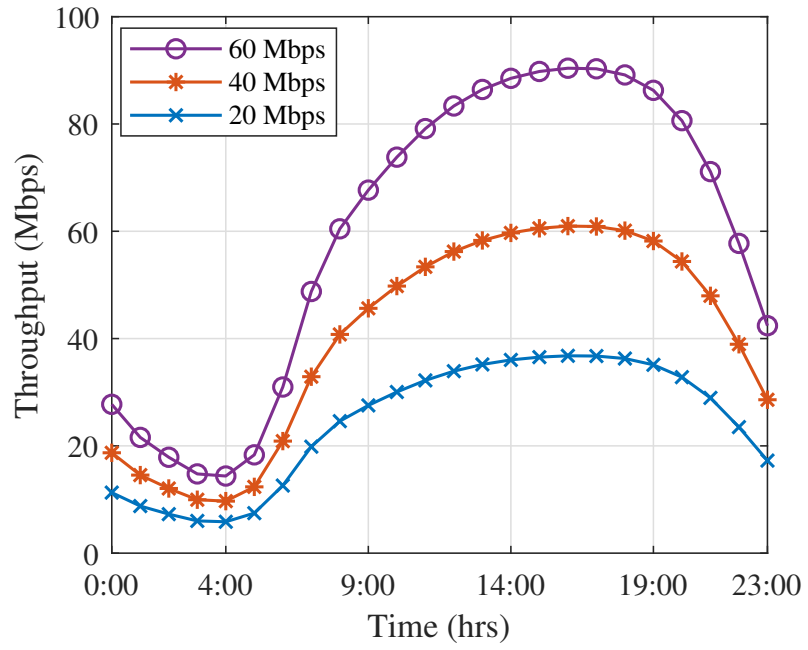


Figure 3.3: Throughput profile of the users.

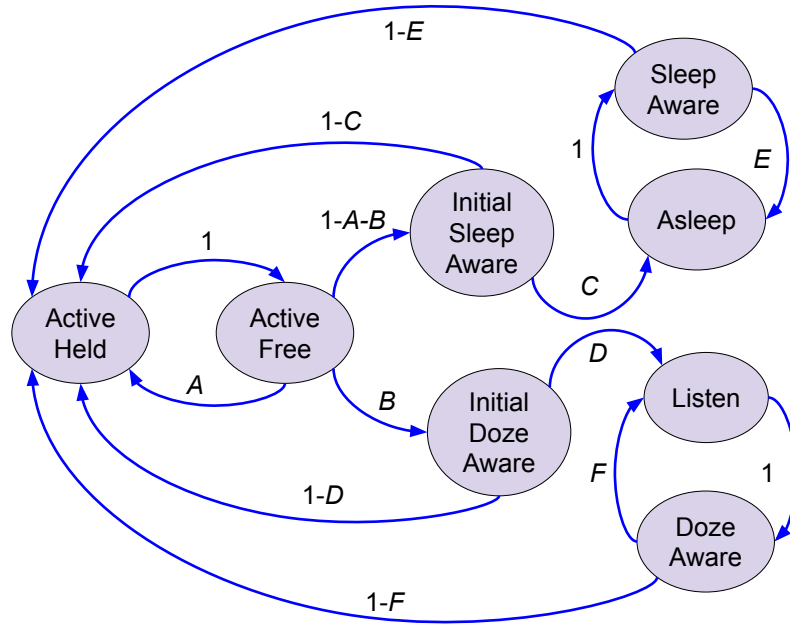


Figure 3.4: State diagram for different states of ONU.

number of users accessing the network is low, the throughput of the network also decreases.

3.3.1 Power Consumption Model

In this subsection, the power consumption profile for FiWi network devices such as ONU and AP are presented. The power consumption of the network devices depends on the throughput profile of the network. The relation between the power consumption and the throughput profile is described in detail below:

3.3.1.1 Power Consumption of ONU

The power consumption of ONU depends on the various power consumption states of ONU. According to [94], the ONU can be in active held state, where ONU is awake and consumes full power, or active free state, where ONU monitors the traffic to decide whether it can go to a low power consumption state, or cyclic sleep state, where both transmitter and receiver are turned off, or doze state, where the transmitter is turned off and the receiver remains turned on or sleep aware state, where ONU checks if there was any traffic, or asleep state where transmitter and receiver are shut down, i.e., state with least power consumption. Let the power consumption of different states of ONU be denoted as sleep aware (P_{sa}), asleep (P_{as}), active held (P_{ah}), doze aware (P_{da}), listen (P_{ls}), and active free (P_{af}), then ONU's power consumption is given as [94]:

$$P_{ONU} = (\gamma_{sa_1}^o + \gamma_{sa_2}^o) P_{sa} + \gamma_{as}^o P_{as} + \gamma_{ah}^o P_{ah} + (\gamma_{da_1}^o + \gamma_{da_2}^o) P_{da} + \gamma_{ls}^o P_{ls} + \gamma_{af}^o P_{af}, \quad (3.3)$$

where, the stationary probabilities for each state is given by γ_{sa}^o , γ_{as}^o , γ_{ah}^o , γ_{da}^o , γ_{ls}^o , and γ_{af}^o , respectively. Moreover, $\gamma_{sa}^o + \gamma_{as}^o + \gamma_{ah}^o + \gamma_{da}^o + \gamma_{ls}^o + \gamma_{af}^o = 1$. Each stationary probability is calculated using state transition probability as given in [94]. The transition probabilities from one state to another is given by A, B, C, D, E , and F as can be seen from Fig. 3.4. A represents the probability active free to active held states, B denotes

Table 3.1: Distribution of transition probabilities [94]

Variable	Expression	Initial state	Final state
A	$1 - \exp(-\delta_u T_{af})$	Active free	Active held
B	$\exp(-\delta_d T_{af})(1 - \exp(-\delta_u T_{af}))$	Active free	Doze aware
C	$\exp(-(\delta_u + \delta_d)T_{sa})$	Asleep	Sleep aware
D	$\exp(-(\delta_u)T_{da})$	Doze aware	Listen
E	$\exp(-(\delta_u + \delta_d)(T_{sa} + T_{as}))$	Sleep aware	Asleep
F	$\exp(-(\delta_u)(T_{da} + T_{ls}))$	Doze Aware	Listen

the probability from active free state to doze aware state. The probability for going to asleep state from sleep aware state is given by C , D denotes the probability for going from doze aware to listen state. E denotes the probability for going from sleep aware to asleep, and F denotes the probability for going from doze aware to listen state for a discrete time Markov chain (DTMC) that represents the power management state of the ONU [94]. The distribution of transition probabilities function from one state to another is further defined in Table 3.1 [94], where δ_u and δ_d are the upstream data rate and downstream data rate, respectively. T_{sa} , T_{as} , T_{ah} , T_{da} , T_{ls} , and T_{af} are the time periods of sleep aware, asleep, active held, doze aware, listen, and active free states of the ONU, respectively. In this work, we consider symmetric data rate scenario, i.e., upstream data rate is equal to downstream data rate, i.e., $\delta_u = \delta_d$ [95], [96]. The burst size for the traffic is considered 450 bytes. Fig. 3.5(a) shows the power consumption of the ONU with respect to the throughput profiles. It is evident that as the throughput increases, the power consumption of the ONU also increases, and the power consumption at 60 Mbps throughput is the highest, followed by 40 Mbps and 20 Mbps.

3.3.1.2 Power Consumption of AP

The energy consumption model for wireless IEEE 802.11 devices also depends on δ_u and δ_d . The power consumption for IEEE 802.11 APs is given as[97]:

$$P_{AP} = P_{idle}^{AP} + P_{Tx}^{AP}T_{Tx}^{AP} + P_{Rx}^{AP}T_{Rx}^{AP} + \gamma_{gx}\delta_d + \gamma_{xr}\delta_u, \quad (3.4)$$

where, P_{idle}^{AP} is the power consumption of AP in the idle mode, P_{Tx}^{AP} and P_{Rx}^{AP} are the transmission and reception power, respectively, T_{Rx}^{AP} and T_{Tx}^{AP} are the reception and transmission airtime percentage, respectively. The cross-factor for reception is denoted by γ_{xr} , i.e., processing toll per-packet in order to deliver the received frame across the protocol stack and γ_{gx} is the cross-factor of the packets generated by the application. The values of $P_{idle}^{AP} = 3.68 \text{ W}$, $P_{Tx}^{AP} = 0.4 \text{ W}$ and $P_{Rx}^{AP} = 0.24 \text{ W}$, $\gamma_{gx} = \gamma_{xr} = 0.93 \times 10^{-3}$ [97]. The airtime percentage for the transmission and reception is also considered to be the same, i.e., $T_{Tx}^{AP} = T_{Rx}^{AP} = 50\%$ [98]. This is because symmetric traffic is useful as it removes the bottleneck on the upstream traffic flow and also provide high data rate for uploading applications. There are many applications that require symmetric uplink and downlink traffic such as, content broadcast, email, file exchange, distance learning, telemedicine, online-games, etc [99]. Fig. 3.5(b) shows the power consumption of the AP according to the throughput. It is evident that as the network throughput increases from 20 Mbps to 60 Mbps, the power consumption of the AP also increases. Further, for the peak traffic hours the power requirement of the AP device is higher than the non-peak traffic hours.

3.3.1.3 Power Consumption of ONU-AP

As mentioned before, the ONU and AP are collectively called ONU-AP. Thus, the power consumption of ONU-AP is the sum of the power consumption of ONU and AP device. Fig. 3.5(c) shows the power consumption of ONU-AP according to the different throughput requirements of the user.

3.3.2 Solar Power Model

The solar irradiance data for the solar power profile at different locations is obtained from National Renewable Energy Laboratory (NREL) [100] as well as an online repository for climate data [101]. The solar irradiance value is fed to the system advisory module (SAM) tool that converts the solar irradiance to an hourly power profile. The considered PV

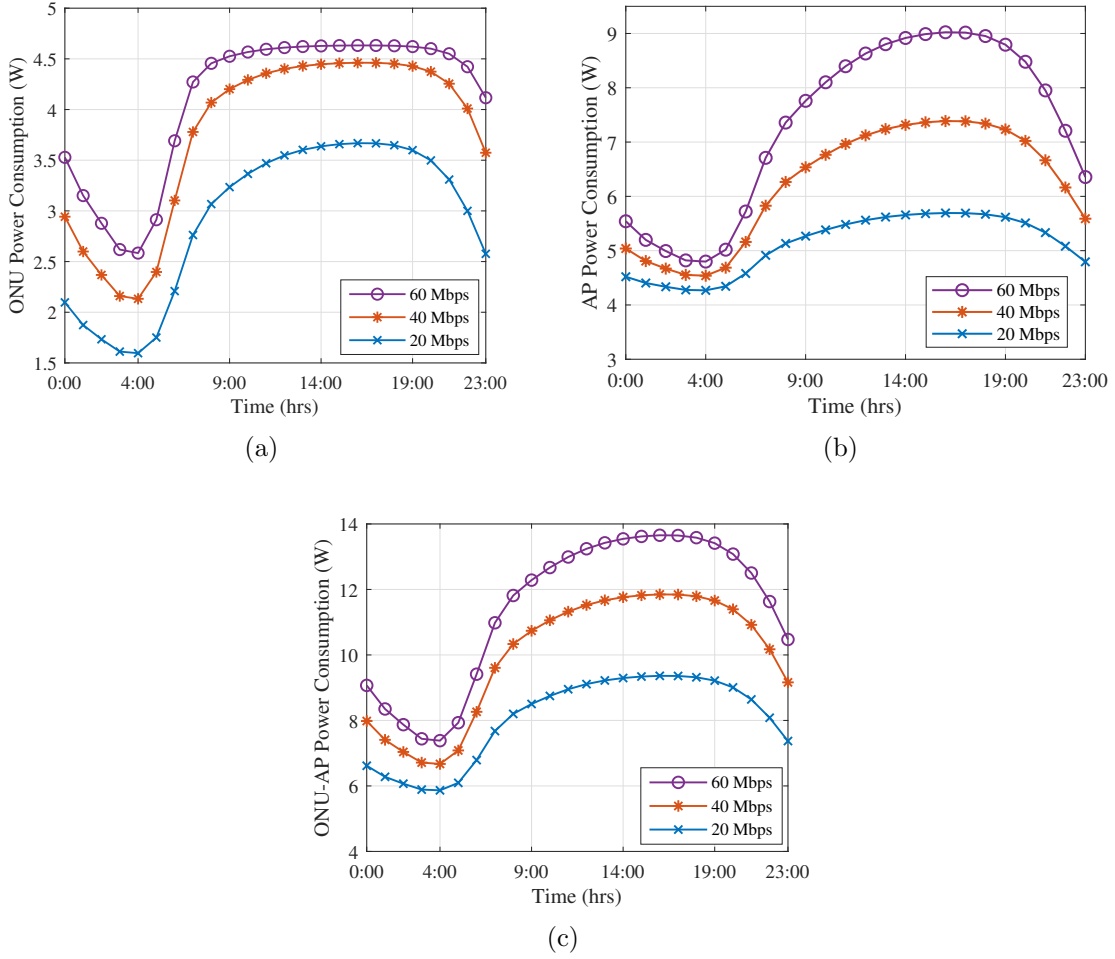


Figure 3.5: Power consumption based on the throughput for a) ONU, b) AP, and c) ONU-AP.

panels have nominal efficiency of 20.55%, an inverter of 0.01 W is used to convert direct Current (DC) to AC with a conversion ratio of 1.2, the inverter efficiency is 96%. The tilt of the PV panels is fixed to 30° in the south direction. The hourly solar power profile is averaged across the year to get the 24-hour average solar profile as shown in Fig. 3.6. It can be seen that different regions have different solar power profiles. The 24-hour aggregated solar power for the three locations are: 45.98 W, 38.11 W, and 27.34 W for Benghazi, Jaipur and Moscow, respectively¹. Benghazi has a better solar profile compared to Jaipur

¹A similar analysis can be extended for other locations as well. For analysis, we have considered the locations based on solar and wind profile, i.e., Benghazi which has good solar as well as wind power, Jaipur which has good solar but low wind power and Moscow which has good wind but low solar power.

and Moscow. For Moscow, solar power is available for a shorter duration of time, and the hourly power profile is also low.

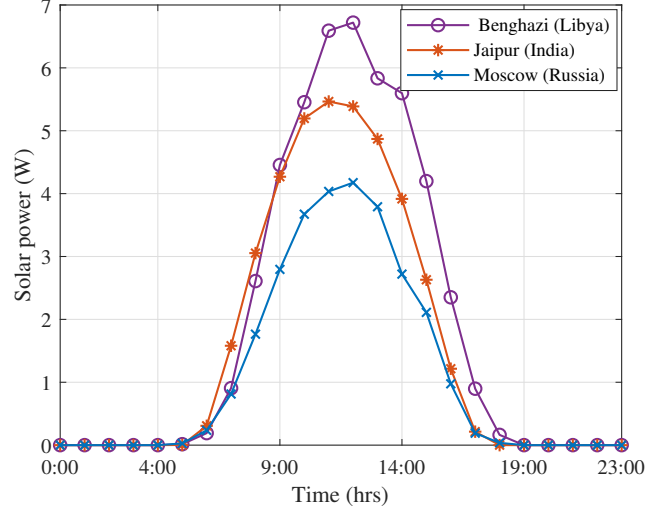


Figure 3.6: Hourly solar power profiles at different locations for 10 W DC rating PV panel.

3.3.3 Rotational PV Panels Solar Power Profile Model

The rotation of PV panels increases the efficiency of the solar power systems. In this work, we consider the rotational PV panels with one-time rotation per day, also known as a two-step solar tracker. Similar to two-step tracker, a concept of three-step solar tracker is mentioned in [102], where authors proposed the rotation of PV panels three times in a day corresponding to morning, noon and evening. We assume that PV panels are directed in the east-west direction, and the panels rotates from east 30° to west 30° at 12:00 hr. Fig. 3.7 shows the power profile of the PV panels with one-time rotation. The solar power profiles at different locations follow the same trend as shown in Fig. 3.6, but due to rotation, the duration of solar power availability as well as the power level increases.

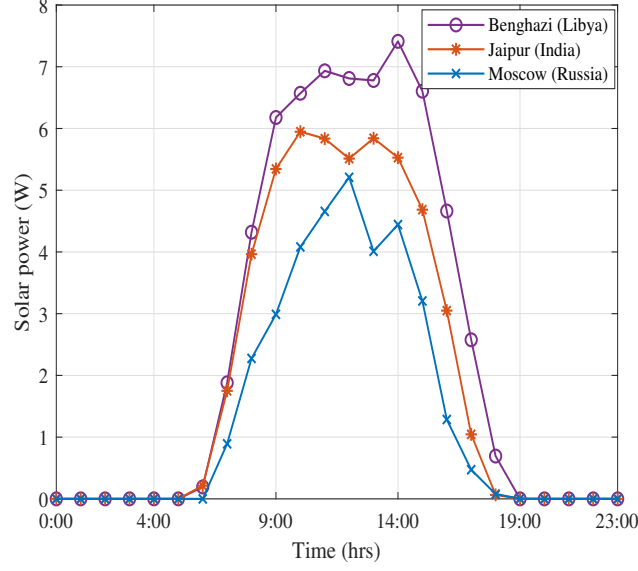


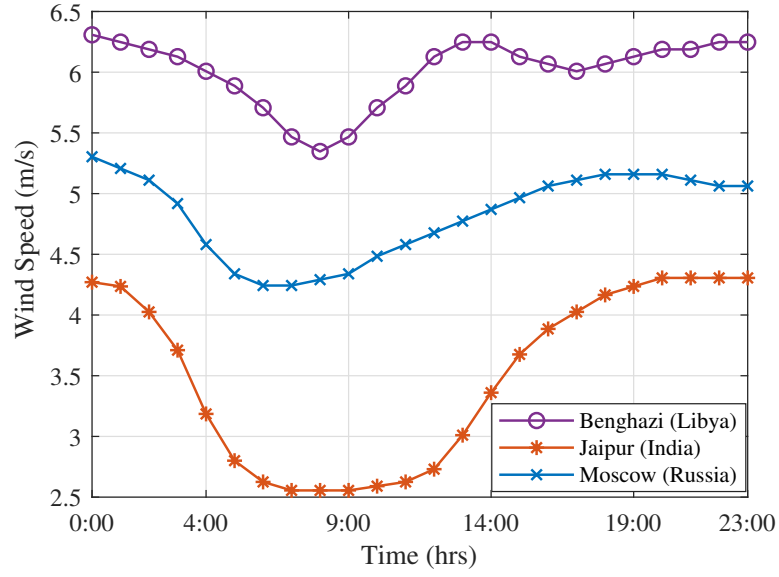
Figure 3.7: Hourly solar power profiles at rotational PV panels at different locations for 10 W DC rating PV panel.

3.3.4 Wind Power Model

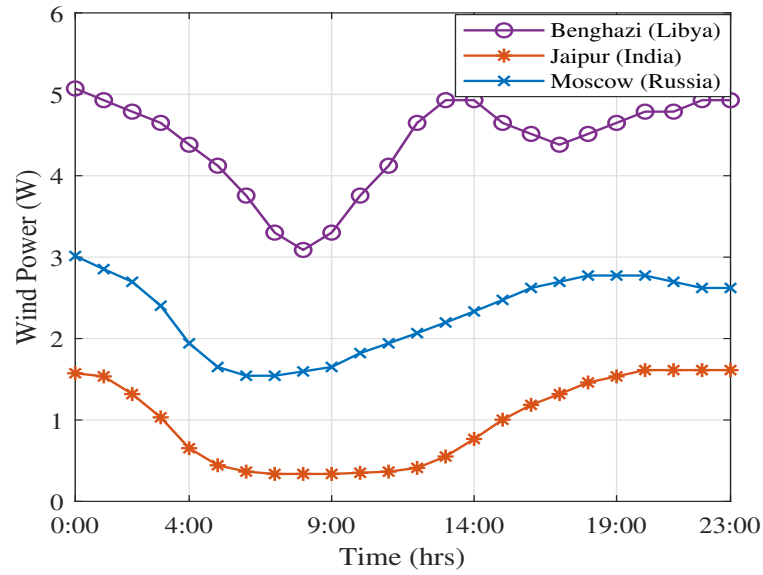
Wind speed depends on the height of the wind-turbine, and the location of installation. The collection of dataset for the wind speed at different locations is available in [103]. According to [103], the wind speed for Benghazi, Jaipur, and Moscow are plotted in Fig. 3.8(a). It is evident that the wind speed at Benghazi is the highest, whereas for Jaipur, the wind speed is the lowest. Based on the wind speed and air density (which in turn is dependent on the height of the wind-turbine), the wind power generated by the wind turbine is given by [104]:

$$P_W = 0.5\rho_a\pi R_w^2 v_w^2 C_{pmax}, \quad (3.5)$$

where, ρ_a is air density, R_w is blade radius of wind machine, v_w is wind speed, and C_{pmax} is the maximum rotor power coefficient. For simulations, we consider $\rho = 1.225 \text{ kg/m}^3$, $R = 0.5 \text{ m}$, $C_{pmax} = 0.042$, and the height of wind turbine as 50 m. The wind power at different locations, namely, Benghazi, Jaipur, and Moscow is shown in Fig. 3.8(b). It is



(a)



(b)

Figure 3.8: a) Wind speed and b) Wind power at different locations.

seen that unlike solar power, wind power is not limited to few hours in a day. For a location like Benghazi, which has high solar power profile, has high wind power profile as well. For Moscow, where the solar power profile is low, the wind power profile is higher compared to Jaipur. Furthermore, the average wind power for a day at Benghazi, Jaipur, and Moscow are 4.4126 W, 0.9721 W, and 2.3045 W, respectively. As shown in Fig. 3.8(b), Benghazi has the highest wind power generation potential, followed by Moscow and Jaipur. The wind power harvesting potential for Jaipur is the lowest.

3.3.5 Battery Model

One of the main energy source required to power the network components when renewable energy source is not available are the batteries. Lead-acid batteries are one of the popular types of batteries because they are cost-effective [105]. Moreover, the partial state of charge has minimal effect on the lifetime of the lead-acid batteries [105]. The batteries have a maximum charging capacity known as battery capacity (P_B^{cap}). Once the state of charge (SoC) of the batteries reaches P_B^{cap} , the batteries cannot be charged further. Moreover, whenever the batteries are discharged or charged, the SoC is updated. The operators generally specify a minimum amount of charge that must be maintained in the batteries known as depth of discharge (DoD). The battery life cycle or lifetime is enhanced if its DoD is maintained to avoid deep discharge i.e., discharge below DoD. The range of DoD is usually restricted to below 50% of the battery capacity [106]. In this work, we have considered a series configuration of batteries, thus, if we consider a deployment scenario with N batteries of P_B^{cap} battery capacity each then, the overall capacity of the string of batteries will be NP_B^{cap} .

3.4 Problem Formulation

A joint optimization problem where the objective is to minimize the energy resource allocated to power ONU-AP is formulated in this section. The batteries and PV panels are used to power ONU-AP, and the PV panels are also used to charge the batteries during the solar hours. It is assumed that at T_H^{th} hour of the day, the SoC of the battery is equal to the battery capacity.

An optimal combination of the number of batteries (N_B) and the number of PV panels (N_{PV}) needs to be calculated based on their total operational cost. Let the total operation cost for the PV panels and batteries be denoted by C_{PV} and C_B , respectively and are given as [22]:

$$C_{PV} = C_{PV}^{asset} + C_{PV}^{O\&M}, \quad (3.6)$$

where, C_{PV}^{asset} is the asset cost of PV panel and $C_{PV}^{O\&M}$ is the operation and management cost (O&M) of the PV panels. The total operational cost of the batteries is given as [22]:

$$C_B = C_B^{asset} + C_B^{O\&M} + N_B^{rep} C_B^{asset}, \quad (3.7)$$

where, C_B^{asset} is the asset cost of the battery, $C_B^{O\&M}$ is the O&M cost of the battery, and N_B^{rep} is the number of times the batteries are needed to be replaced during the lifetime of the system.

In this work, all the analysis is done on hourly basis, i.e. for $t \in [0, 23]$ hour. The hourly solar power profile for single PV panel is given by $P_S^1(t), \forall t \in [0, 23]$. Similarly, the state of charge of a single battery is denoted by $P_{SoC}^1(t), \forall t \in [0, 23]$. The DoD limit for each battery is denoted by βP_B^{cap} . Consequently, the hourly power consumption of ONU-AP is defined by $P_{ONU-AP}(t), \forall t \in [0, 23]$.

The optimization problem thus formulated is given as:

$$(P1) \min_{N_{PV}, N_B} N_{PV}C_{PV} + N_B C_B, \quad (3.8)$$

$$s.t. \beta P_B^{cap} \leq P_{SoC}^1(t) \leq P_B^{cap}, \quad \forall t \in [0, 23], \quad (3.9)$$

$$P_{SoC}^1(T_H) \geq P_B^{cap}, \quad (3.10)$$

$$N_{PV}P_S^1(t) + N_B P_{SoC}^1(t) \geq P_{ONU-AP}(t), \quad \forall t \in [0, 23]. \quad (3.11)$$

Here, (3.8) represents the optimization function to minimize the overall cost of the system, where, $N_B, N_{PV} \in \mathbb{Z}$. The first constraint in (3.9), is used to maintain the charge in the battery between βP_B^{cap} and P_B^{cap} . The second constraint in (3.10) denotes that each battery must be entirely charged at T_H^{th} hour of the day. The third constraint in (3.11) represents that for each hour, the power from N_B batteries and N_{PV} PV panels must be able to fulfill the power demand of ONU-AP.

It should be noted that (3.8) is a linear integer objective function, where, the optimization variables $N_{PV}, N_B \in \mathbb{Z}$. However, due to the last constraint in (3.11) which is quadratic in nature, the optimization problem is a quadratic constraint linear programming problem (QCLP) [107], which is a special case of quadratic constraint quadratic programming problem (QCQP) [108]. In order to find an optimal solution for problem (P1), the quadratic constraint in (3.11) could be converted to separable variables as discussed in [109]. However, even if the last constraint in (3.11) is converted to separable variable form, the problem is still non-linear and the Hessian matrix will have positive and negative eigenvalues. Thus, the problem will not have any global maximum or minimum. Therefore, in order to solve this problem, we propose a two-step iterative approach [107], which is discussed in detail in Section V.

3.5 Proposed Method for Joint Energy Resource Allocation

In this section, we describe the two-step iterative algorithm to get a solution for the non-convex problem. First, we present the algorithm for minimizing the number of batteries required by ONU-AP. Later, we present the algorithm for minimizing the number of PV panels required to power ONU-AP and charge the batteries required by ONU-AP. Finally, we present an iterative algorithm to converge the number of PV panels and batteries needed by ONU-AP².

3.5.1 Algorithm To Calculate Minimum Number of Batteries

In this subsection, the algorithm to calculate minimum number of batteries required by the ONU-AP is presented. As the work considers an off-grid environment, the batteries are used to power ONU-APs when solar power is unavailable. The Algorithm 1, considers a heuristic method where the battery power changes for each loop. Considering that at each iteration of the loop the total battery capacity, $P_B^{cap,N}$ increases in the multiple of single battery capacity P_B^{cap} .

As discussed earlier, the batteries should be charged by the PV panel at T_H^{th} hour. Therefore, we initialize the battery power at T_H^{th} hour, $P_B(T_H) = P_B^{cap}$. For each hour t , the power is drawn from the PV panel, $P_S(t)$ is calculated as:

$$P_S(t) = \min \{P_{ONU-AP}(t), P_S^M(t)\}, \quad (3.12)$$

where, $P_S^M(t)$ is the power of the PV panel at time t . Now, we check whether the power

²The energy resource allocation for FiWi network consisting of XG-PON and WLAN is proposed in this work. However, the change of technology from GPON to EPON or WLAN to other wireless technology, such as WiMAX or WMN, would not alter the operation of the proposed algorithm. The proposed algorithm is agnostic to FiWi framework employed.

from PV panels is sufficient to charge to ONU-AP:

$$P_{ONU-AP}(t) - P_S(t) = \begin{cases} \leq 0, & \text{if the power is sufficient} \\ > 0, & \text{if the power is deficit} \end{cases} \quad (3.13)$$

In case the power from the PV panel is not sufficient, the deficit power supplied by the batteries is given as:

$$P_{def}(t) = P_{ONU-AP}(t) - P_S(t), \quad (3.14)$$

otherwise, $P_{def}(t) = 0$. Similarly, in cases where power from PV panels is not sufficient to power ONU-AP, there will be no excess power available with the PV panel, $P_S^{ex} = 0$. Otherwise, the excess power from the PV panel is given as follows:

$$P_S^{ex} = P_S^M(t) - P_S(t). \quad (3.15)$$

In order to satisfy the constraint in (3.9), the power of each battery at each hour t , must be in between βP_B^{cap} and P_B^{cap} . Thus, it is necessary that the power in the battery allocated for the next hour of operation $P_{SoC}(t+1) = P_{SoC}(t) - P_{def}(t) + P_S^{ex}(t)$ is not below $\beta P_B^{cap,N}$ or more than $P_B^{cap,N}$. Therefore, the number of times in a day the battery power is going below $\beta P_B^{cap,N}$ is counted using a variable $P_o(t)$, which is 1 every time the battery power is below $\beta P_B^{cap,N}$. The algorithm stops once, B_{cap} is enough to satisfy that the battery does not discharge beyond $\beta P_B^{cap,N}$ at any time t . Algorithm 1 presents the algorithm to calculate the minimum number of batteries required by ONU-APs without any deep discharge. The complexity of Algorithm 1 is calculated as $\mathcal{O}(Count_B)$.

3.5.2 Algorithm To Calculate Minimum Number of PV Panels

As we consider an off-grid scenario thus, the batteries can only be charged by the PV panels. The PV panels are used to power ONU-AP as well as charge the batteries for

Algorithm 1 The battery allocation algorithm

Input: $Count_{PV}$ = Number of PV panels**Initialize:**

$$P_{SoC}(T_H) = P_B^{cap}$$

 $P_o = 1 \times 24$ vector with all values = 1

$$Count_B = 1$$

$$P_S^M = Count_{PV} \times P_S^1$$

```
1: while  $\sum_{t=0}^{23} P_o(t) = 0$  do
2:   for  $t = T$  to  $T + 23$  do
3:      $P_B^{cap,N} = Count_B \times P_B^{cap}$ 
4:      $P_S(t) = \min\{P_{ONU-AP}(t), P_S^M(t)\}$ 
5:     if  $P_{ONU-AP}(t) - P_S(t) > 0$  then
6:        $P_{def}(t) = P_{ONU-AP}(t) - P_S(t)$ 
7:        $P_S^{ex}(t) = 0$ 
8:     else
9:        $P_{def}(t) = 0$ 
10:       $P_S^{ex}(t) = P_S^M(t) - P_S(t)$ 
11:    end if
12:    if  $P_{SoC}(t+1) - P_{def}(t) + P_S^{ex}(t) < \beta P_B^{cap,N}$  then
13:       $P_o(t) = 1$ 
14:    else
15:       $P_o(t) = 0$ 
16:    end if
17:     $P_{SoC}(t+1) = \min\{P_{SoC}(t) - P_{def}(t) + P_S^{ex}(t), P_B^{cap,N}\}$ 
18:  end for
19:   $Count_B = Count_B + 1$ 
20: end while
```

Output: The value of $Count_B$ is the minimum batteries required by ONU-AP for $Count_{PV}$ PV panels.

operation during non-solar hours. To calculate the minimum number of PV panels required by ONU-AP, we propose Algorithm 2, as discussed below. The batteries must be completely charged at T_H^{th} hour, for this, consider the power supplied by the PV panel to ONU-AP given as:

$$P_S(t) = \min \{P_{ONU-AP}(t), P_S^M(t)\}. \quad (3.16)$$

If the power supplied by the PV panels is not enough to fulfill the power demand of ONU-AP, the power needs to be extracted from the batteries. The deficit power supplied

Algorithm 2 The PV panel allocation algorithm

Input:

$Count_B$ = Number of batteries

Initialize:

$$P_{SoC}^N(T_H) = Count_B \times P_B^{cap}$$

$P_o = 1 \times 24$ vector with all values = 1

$$Count_{PV} = 1$$

$$P_B^{cap,N} = Count_B \times P_B^{cap}$$

```

1: while  $P_{SoC}(T_H + 24) = P_B^{cap,N}$  do
2:   for  $t = T$  to  $T + 23$  do
3:      $P_S^M(t) = Count_{PV} \times P_S^1(t)$ 
4:      $P_S(t) = \min\{P_{ONU-AP}(t), P_S^M(t)\}$ 
5:     if  $P_{ONU-AP}(t) - P_S(t) > 0$  then
6:        $P_{def}(t) = P_{ONU-AP}(t) - P_S(t)$ 
7:        $P_S^{ex}(t) = 0$ 
8:        $P_{min} = \min\{P_{SoC}(t) - P_{def}(t) + P_S^{ex}(t), P_B^{cap,N}\}$ 
9:        $P_{SoC}^N(t + 1) = \max\{P_{min}, \beta P_B^{cap,N}\}$ 
10:    else
11:       $P_{def}(t) = 0$ 
12:       $P_S^{ex}(t) = SP(t) - P_S(t)$ 
13:       $P_{min} = \min\{P_{SoC}^N(t) - P_{def}(t) + P_S^{ex}(t), P_B^{cap,N}\}$ 
14:       $P_{SoC}^N(t + 1) = \max\{P_{min}, \beta P_B^{cap,N}\}$ 
15:    end if
16:  end for
17:   $Count_{PV} = Count_{PV} + 1$ 
18: end while

```

Output: The value of $Count_{PV}$ is the minimum PV panels required by ONU-AP for $Count_B$ batteries.

by the batteries is given as:

$$P_{def}(t) = \begin{cases} 0, & \text{if } P_{ONU-AP}(t) - P_S(t) \leq 0 \\ P_{ONU-AP}(t) - P_S(t), & \text{otherwise.} \end{cases} \quad (3.17)$$

Further, in order to satisfy constraint in (3.9), we need to check the battery state at the beginning of the next hour. The battery state, $P_{SoC}(t + 1)$ must be between $\beta P_B^{cap,N}$ and $P_B^{cap,N}$. The battery power state at the beginning of the next hour $P_{SoC}^N(t + 1)$ is given as follows:

$$P_{min} = \min\{P_{SoC}^N(t) - P_{def}(t) + P_S^{ex}(t), P_B^{cap,N}\}, \quad (3.18)$$

$$P_{SoC}^N(t+1) = \max\{P_{min}, \beta P_B^{cap,N}\}. \quad (3.19)$$

The constraint in (3.10) must be met in order to entirely charge the batteries at the beginning of next T_H^{th} hour:

$$P_{SoC}^N(T_H + 24) = P_B^{cap,N}. \quad (3.20)$$

The number of PV panels for which (3.20) is met, gives the minimum number of PV panels required by the system. Similar to Algorithm 1, the complexity of Algorithm 2 is: $\mathcal{O}(Count_{PV})$.

3.5.3 Iterative Approach

The iterative algorithm for solving the optimization problem (3.8) is based on a two-way iteration between minimum batteries and minimum PV panels and is described concisely in Algorithm 3 [110]. Initially, we fix the number of batteries to N_B (Here, we have initialized the algorithm with fixed number of batteries, however, we could also initiate with fixed number of PV panels). For N_B batteries, we calculate the minimum number of PV panels required to power the ONU-AP. For the calculated number of PV panels, we calculate the minimum number of batteries. This process goes on until converges is obtained, i.e., number of batteries and PV panels calculated from the current iteration, $(k+1)^{th}$ is equal to the number of batteries and PV panels of previous iteration, i.e., k^{th} iteration. For Algorithm 3, the iterative approach iterates Algorithm 1 and Algorithm 2 until convergence. Thus, the complexity of Algorithm 3 is: $\mathcal{O}(k(Count_B + Count_{PV}))$, where k denotes the number of iterations after which the algorithm converges.

Algorithm 3 The iterative algorithm

Initialize: The number of batteries, N_B to a random integer

- 1: Calculate the minimum number of PV panels (N_{PV}) required to power ONU-AP and charge the N_B batteries at the T_H^{th} hour
 - N_{PV} = The PV panel allocation algorithm (N_B)
 - 2: Calculate the minimum number of batteries (N_B) required to power ONU-AP given N_{PV} PV panels
 - N_B = The battery allocation algorithm (N_{PV})
 - 3: Go back to step 1 and iterate until convergence.
-

Table 3.2: Duration of solar power profile available to power ONU-AP

	Case I: Batteries + fixed PV panels	Case II: Batteries + rotational PV panels	Case III: Batteries + fixed PV panels + wind turbine	Case IV: Batteries + rotational PV panels + wind turbine
Benghazi	6:45 to 17:00	6:45 to 18:00	7:00 to 17:45	7:00 to 17:45
Jaipur	6:45 to 17:15	6:45 to 17:30	6:45 to 17:15	6:45 to 17:15
Moscow	6:45 to 17:00	6:45 to 17:15	6:45 to 17:00	6:45 to 17:15

3.6 Analytical Framework

The power in the batteries must be able to fulfill the demand of ONU-AP during non-solar hours, P_{NS}^{ONU-AP} . Considering the battery capacity of a single battery as P_B^{cap} , the power available by the batteries to charge ONU-AP is given by $P_B^{cap} - \beta P_B^{cap}$. Therefore, the number of batteries required by ONU-AP, N_B is given as:

$$N_B(P_B^{cap} - \beta P_B^{cap}) = P_{NS}^{ONU-AP}, \quad (3.21)$$

$$N_B = \frac{P_{NS}^{ONU-AP}}{(P_B^{cap} - \beta P_B^{cap})}, \quad (3.22)$$

$$N_B = \frac{P_{NS}^{ONU-AP}}{(1 - \beta)P_B^{cap}}. \quad (3.23)$$

The PV panel power available to the batteries is given as:

$$P_{PV}^{Bat} = \sum_{i=0}^{23} P_S^M(i) - P_S^{ONU-AP}, \quad (3.24)$$

where, P_S^{ONU-AP} is the power of PV panel consumed during solar hours and P_S^M is the hourly solar power profile of N_{PV} PV panels. (3.25) can be rewritten as:

$$P_{PV}^{Bat} = N_{PV} \sum_{i=0}^{23} P_S^1(i) - P_S^{ONU-AP}, \quad (3.25)$$

where, N_{PV} be the minimum number of PV panels required by ONU-AP and P_S^1 is the hourly solar power profile of a single PV panel.

It is well known fact that PV panel power can be used to charge the batteries. Thus, the power of the PV panels available to the batteries must be equal to the power available by the batteries to charge the ONU-AP, i.e.:

$$P_{PV}^{Bat} - N_B(P_B^{cap} - \beta P_B^{cap}) = 0, \quad (3.26)$$

$$P_{PV}^{Bat} = N_B(P_B^{cap} - \beta P_B^{cap}). \quad (3.27)$$

Using (3.25), (3.27) can be written as:

$$N_{PV} \sum_{i=0}^{23} P_S^1(i) - P_S^{ONU-AP} = N_B(P_B^{cap} - \beta P_B^{cap}), \quad (3.28)$$

$$N_{PV} = \frac{N_B(P_B^{cap} - \beta P_B^{cap}) + P_S^{ONU-AP}}{\sum_{i=0}^{23} P_S^1(i)}. \quad (3.29)$$

Depending on the locations, the duration of solar power supplied to ONU-AP also varies. Table 3.2 summarizes the considered duration of solar power availability to fulfill the demand of ONU-AP. For instance, Benghazi has a good solar profile, thus, the duration for which the PV panels can supply power to ONU-AP is also longer, while for the location

such as Moscow, the solar power supplied to ONU-AP is for a short duration. Similarly, with rotational PV panels, the duration of solar power profile available to power ONU-AP is higher compared to fixed PV panels. An increase in one hour solar power duration for Benghazi can be observed from Table 3.2 due to rotational PV panels. Furthermore, with the introduction of wind power, the effective power consumed by ONU-AP from PV panels and batteries reduces, thus PV panel might be able to charge ONU-AP even during the low solar power hours and the effective duration for which PV panels can supply power to the ONU-AP increases. For instance, an increase of 30 min solar power duration for Benghazi because of high wind power, but at Jaipur and Moscow there is no increase in the duration of solar power supply as the wind power at Jaipur and Moscow is low. Similarly, it is interesting to observe that with the installation of both the wind turbines and rotational PV panels, the duration for which solar power supply is available to power ONU-AP further increases.

3.7 Performance Evaluation

In this section, the performance of the iterative and analytical approach to minimize the energy resources required to power ONU-AP is discussed. The energy resource allocation scheme for four different cases are compared: a) Case I: Batteries with fixed PV panels, b) Case II: Batteries with rotational PV panels, c) Case III: Batteries with fixed PV panels and wind turbine, and d) Case IV: Batteries with rotational PV panels and wind turbine. For wind power, we consider a wind turbine with parameters specified in Section II. The capacity of the single battery is considered to be 5W [111]. The DC power rating of a single PV panel is 5W [112]. Moreover, for analysis, we consider that at time $T = 16:00$ hrs the PV panels entirely charge the batteries. The DoD value for the battery, β is considered 0.7 [19].

3.7.1 Iterative And Analytical Approach

This subsection presents the results for the iterative approach and compares the results from the algorithm with the analytical framework proposed in Section V.

Fig. 3.9 shows the minimum number of PV panels and batteries required to power an ONU-AP for case I when the batteries and fixed PV panels are installed to power ONU-AP. Considering the assumptions mentioned in Table 3.2, it can be observed that the theoretical values for the number of PV panels and batteries is in agreement with the results from the two-way iterative approach. Moreover, as the throughput increases, the number of PV panels and batteries required by ONU-AP also increases. This is because, with the increase in throughput, the power consumption of ONU-AP increases, therefore, more batteries and PV panels are required by ONU-AP. Further, it can be observed that for Benghazi, where the solar power profile is higher compared to Jaipur and Moscow, the number of PV panels and batteries required by ONU-AP is less compared to other cities. For instance, for 20 Mbps throughput, the number of PV panels and batteries required at Benghazi are 30 and 9, respectively, whereas the number of PV panels and batteries required at Moscow increases to 31 and 15, respectively.

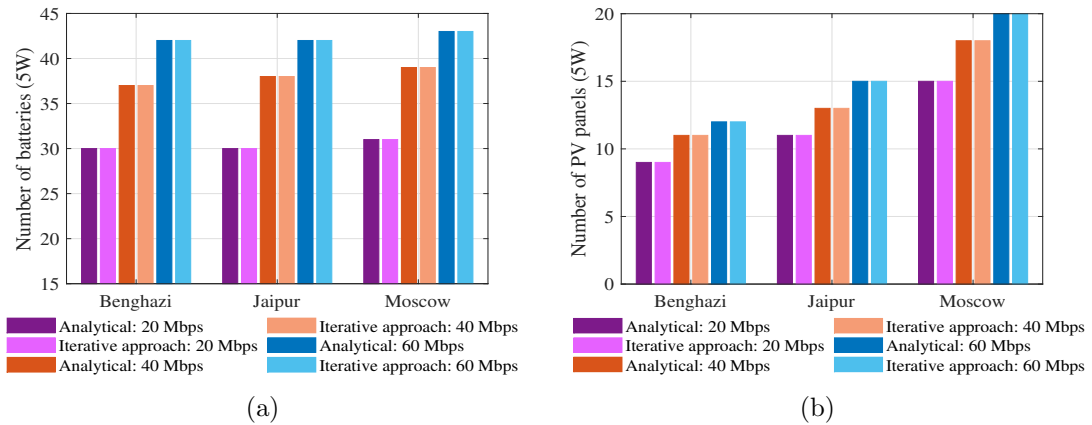


Figure 3.9: Minimum a) Number of batteries and b) Number of PV panels for Case1: Batteries with fixed PV panels.

Fig. 3.10 presents the minimum number of PV panels and batteries required to power

ONU-AP for case II, i.e. when the batteries with rotation PV panels are installed to power ONU-AP. The analytical values are in consensus with the proposed algorithm results, verifying the accuracy of the iterative approach. Further, it is evident that with the increase in throughput, the number of PV panels and batteries required by ONU-AP also increases. For instance, an increase of 10 batteries and 2 PV panels can be observed as the throughput increases from 20 Mbps to 60 Mbps at Benghazi. Further, a clear impact on the allocation of energy resources can be seen as the location of installation changes from higher solar profile location to lower solar profile location. Moreover, compared to Fig. 3.9, utilizing rotation of PV panels reduces the number of batteries from 30 to 27 at Benghazi for 20 Mbps throughput, and the number of PV panels are reduced from 9 to 7.

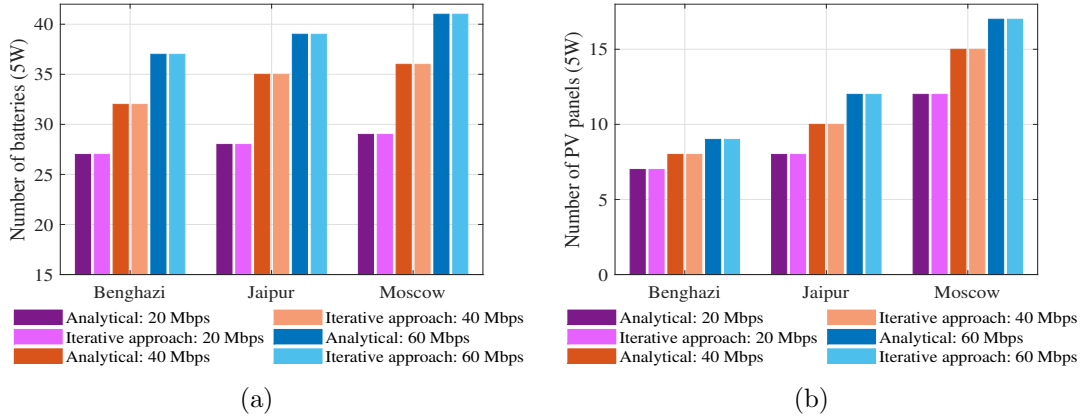


Figure 3.10: Minimum a) Number of batteries and b) Number of PV panels for Case II: Batteries with rotational PV panels.

Fig. 3.11 shows the impact of the installation of wind turbines with fixed PV panels and batteries for analytical and iterative approach. The results for iterative approach are in agreement with the analytical results. Compared to case I, the number of PV panels and batteries is reduced significantly. As the wind power is not limited to a certain number of hours in a day thus, the effective power requirement of ONU-AP consumed via batteries and PV panels reduces, and with the reduction in power consumption of ONU-AP, the

energy resource allocation also reduces. The number of batteries reduces from 30 to 12 at Benghazi for 20 Mbps throughput with the introduction of wind turbines. Similarly, a reduction of 5 PV panels can be observed with the installation of wind turbines. It can be observed that the wind power for Benghazi is the highest; thus, a saving of $>50\%$ of the batteries and PV panels can be seen compared to case I, while, for Jaipur, there is only a saving of 5-6 batteries and 1-2 PV panels because wind power is the lowest for Jaipur, and for Moscow, there is a reduction of 8 batteries and 3-4 PV panels. Thus, it can be inferred that the reduction in the energy resource requirement is proportional to the amount of wind power harvested at the location.

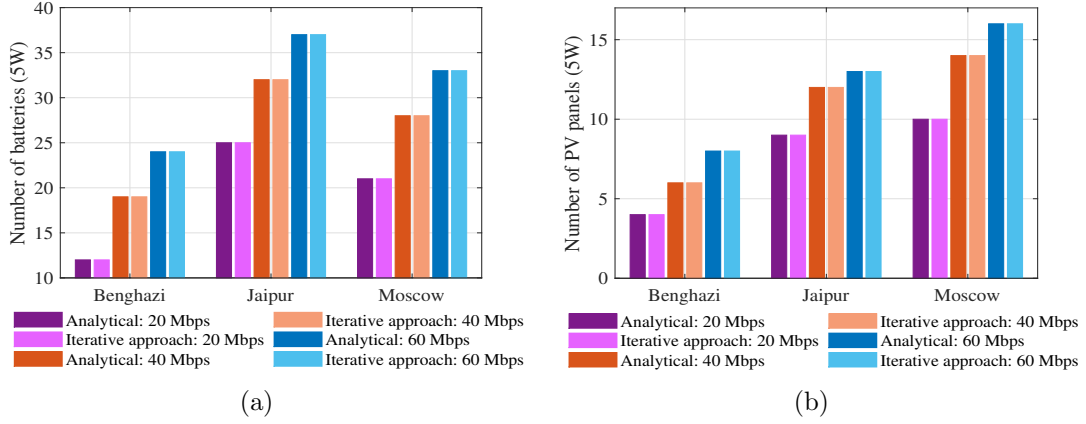


Figure 3.11: Minimum a) Number of batteries and b) Number of PV panels for Case III: Batteries with fixed PV panels and wind turbine.

For case IV, where batteries along with rotational PV panels and wind turbine are installed at ONU-AP, the number of PV panels and batteries reduces further as can be seen from Fig. 3.12. Further, it can be seen that the number of batteries reduces from 42 to 22, and the number of PV panels reduces from 12 to 6 for case IV compared to case I at Benghazi for 60 Mbps throughput. Moreover, compared to case II, there is a reduction of 15 batteries and 3 PV panels for 60 Mbps throughput at Benghazi.

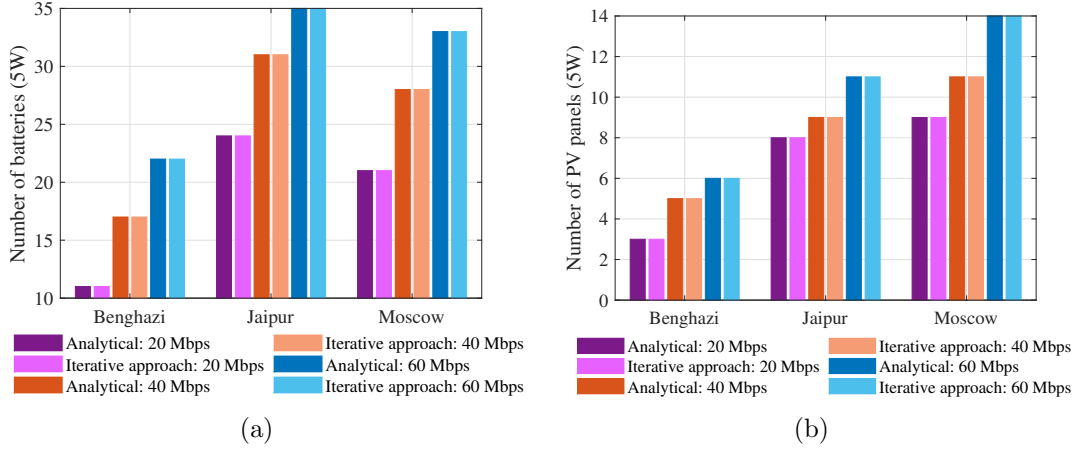


Figure 3.12: Minimum a) Number of batteries and b) Number of PV panels for Case IV: Batteries with rotational PV panels and wind turbine.

3.7.2 Cost Analysis

In this subsection, we evaluate the cost analysis of the resource required to power the ONU-AP. The cost for batteries and PV panels are calculated using (3.7) and (3.30), respectively. The asset cost of the batteries $C_B^{asset} = \$195/kWh = \$4.680/W$ for a day, the O&M cost of the batteries are, $C_B^{O\&M} = 2\%$ of C_B^{asset} [22]³, the lifetime of the batteries is assumed to be 5 yrs [113], thus for a system lifetime of 20 yrs, there is a need to replace the batteries three times, therefore, $N_B^{rep} = 3$, the asset cost for the PV panels and wind turbines are $C_{PV}^{asset} = \$3000/kWh = \$72/W$ for a day and $C_W^{asset} = \$2500/kWh = \$60/W$ for a day, respectively and the O&M cost is 2% of the asset cost [22]. The cost of the wind turbine is calculated as:

$$C_W = C_W^{asset} + C_W^{O\&M}, \quad (3.30)$$

The lifetime of PV panels and wind turbines is considered 20 yrs, therefore, no replacement for the PV panels and wind turbine is considered for analysis [22]. Table 3.3 shows the

³However, these cost might vary depending on the country. For this work, we have used the cost given in [22].

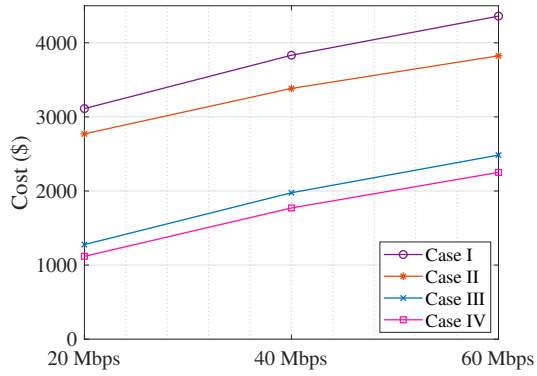
Table 3.3: Cost and CO₂ emission analysis of batteries and PV panels

	Battery	PV panel	Wind turbine
Cost (\$/W)	20.562	4.20	3.520
CO ₂ emissions (g/W) [24]	4.22	0.96	0.96

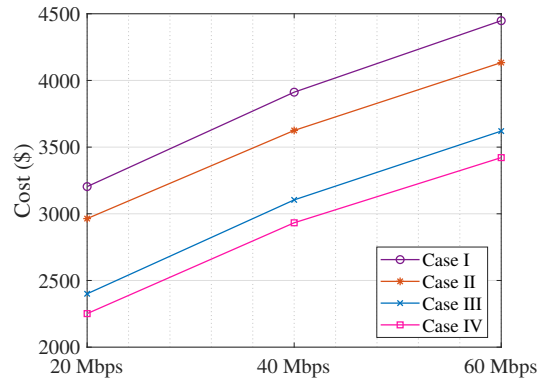
cost of batteries, PV panels and wind turbine. In terms of overall cost, the batteries are costlier compared to the PV panels, and the wind turbines are the cheapest. The cost of PV panel motor for rotation of the PV panel is considered to be \$0.1/W [114].

In Fig. 3.13, the cost analysis at different locations is shown. It can be observed from Fig. 3.13(a), that for case I, i.e., where the batteries are installed along with non-rotation PV panels has the highest cost for Benghazi followed by the case where batteries along with rotation PV panels. This is because the number of PV panels and batteries are reduced due to rotation of PV panels. For case III, where wind turbines are installed with PV panels without rotation the cost reduces from \$3112 to \$1276.25, which further reduces to \$1117.75 for case IV. Moreover, it can be seen that for case III and IV, the reduction in cost with respect to case I and II is significant because of the installation of wind turbines.

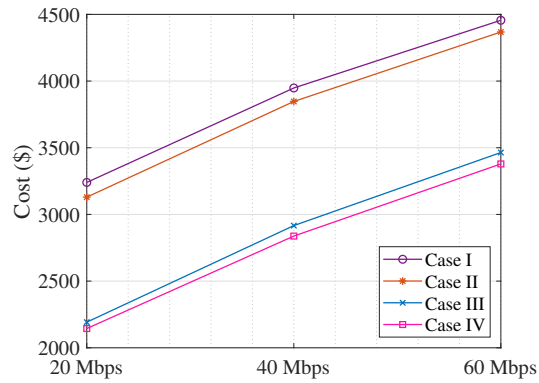
A similar trend can be observed in Figs. 3.13(b) and 3.13(c). It is evident that as the wind power in Benghazi is higher compared to Jaipur and Moscow, the reduction in the cost due to the installation of the wind turbine is greater for Benghazi compared to Jaipur and Moscow. A clear difference of \$1835.75 is observed at Benghazi for 20 Mbps throughput between the cost with and without wind turbine with fixed PV panel and batteries, while that for Jaipur and Moscow is \$511.75 and \$947.75 for 20 Mbps throughput. Moreover, it can also be observed that the difference due to the rotation of PV panels, i.e., case I and case II, and case III and case IV, decreases with the change in location from Benghazi to Moscow to Jaipur. This is because the wind power in Benghazi is high compared to Moscow and Jaipur.



(a)



(b)



(c)

Figure 3.13: Cost analysis for a) Benghazi, b) Jaipur, and c) Moscow for Case I: Batteries with fixed PV panels, Case II: Batteries with rotational PV panels, Case III: Batteries with fixed PV panels and wind turbine, and Case IV: Batteries with rotational PV panels and wind turbine.

3.7.3 Carbon Footprint Analysis

In this subsection, we evaluate the environmental impact of the energy resource allocation scheme in terms of CO₂ emissions. The CO₂ emissions for batteries, wind turbine and PV panels are mentioned in Table 3.3. The batteries have the highest CO₂ emissions, followed by PV panels and wind turbines. The CO₂ emissions from the proposed solution are compared to the traditional grid power supply. The grid power can have a contribution from different energy sources such as thermal power, coal-based stations, gas-based stations, etc. According to the report by the Central Electricity Authority, India on CO₂ baseline Database for the Indian power sector, 2018, the weighted average emission factor CO₂ emission for India is 0.82 t CO₂/MWh in 2017-18 [115]. The different components of CO₂ emission is mentioned in Table 3.4. Similarly, for Russia and Libya the CO₂ emissions are 0.39 t CO₂/MWh and 0.983 t CO₂/MWh, respectively [116], [117].

Table 3.4: Weighted average specific CO₂ emissions from the different fossil fuel stations for India in 2017-18 [115]

Energy sources	CO ₂ Emissions
Coal-based stations	0.97 t CO ₂ /MWh
Diesel-based stations	0.70 t CO ₂ /MWh
Gas-based station	0.45 t CO ₂ /MWh
Lignite based stations	1.36 t CO ₂ /MWh

The environmental impact in terms of CO₂ emission for Benghazi, Jaipur, and Moscow is shown in Fig. 3.14. It can be seen that in the case of only grid power supply, the CO₂ emissions are the highest. For Benghazi at 40 Mbps, a CO₂ reduction of 96.8 g can be observed for case II compared to case I due to installation of rotational PV panels, and a reduction of 295.99 g due to installation of wind turbine along with fixed PV panels compared to case I. Similarly, for Jaipur, case IV has the least CO₂ emission of 702.81 g, while for case I the CO₂ emission of 841.98 g can be observed. For Moscow, a reduction of 50.08 g, 164.44 g, and 188.62 g can be observed for case II, III and IV compared to case I. Furthermore, a significant reduction of 91.61%, 86.17%, and 70.86% CO₂ emissions

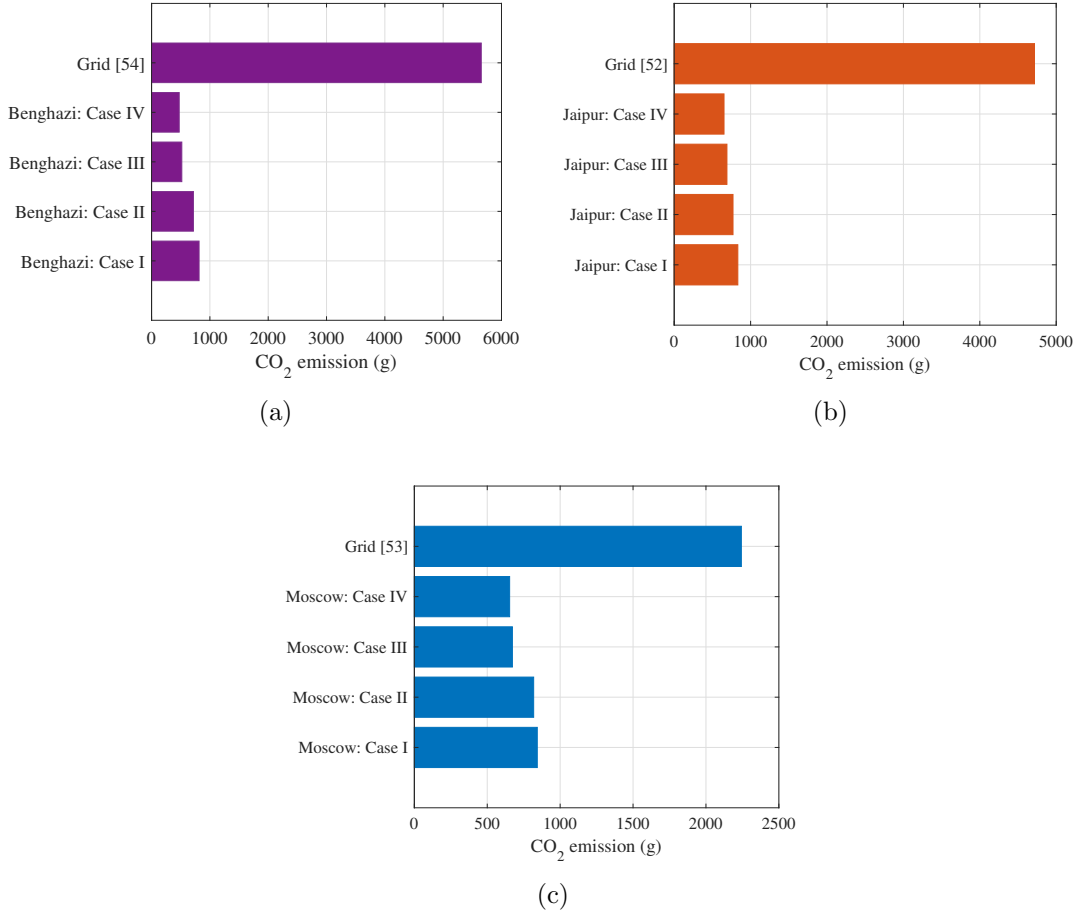


Figure 3.14: CO₂ emission analysis for a) Benghazi, b) Jaipur, and c) Moscow at 40 Mbps for Case I, Case II, Case III, Case IV, and grid.

is evident for Benghazi, Jaipur and Moscow, respectively by using batteries along with rotational PV panels and wind turbine in place of traditional grid power supply.

3.7.4 Trade-Off Analysis Between Allocation Efficiency And Cost

In this subsection, we analyze the trade-off between allocation efficiency and cost, which is an important factor for the allocation of resources to power the ONU-AP. The allocation efficiency can be analyzed as an outage, i.e., the number of times the system is not able to fulfill the power of the ONU-AP or the number of times the battery level goes below the depth of discharge value [18]. The lower the outage, the higher the allocation efficiency.

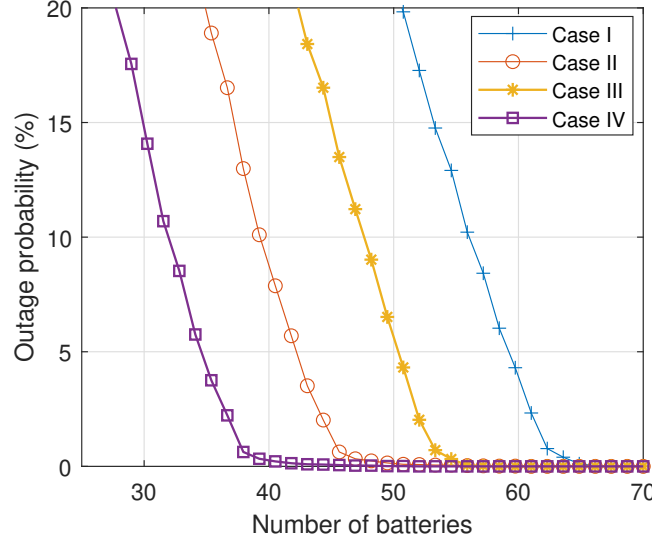


Figure 3.15: Outage analysis for Jaipur at 40 Mbps throughput for Case I: Batteries with fixed PV panels, Case II: Batteries with rotational PV panels, Case III: Batteries with fixed PV panels and wind turbine, and Case IV: Batteries with rotational PV panels and wind turbine.

In order to achieve a lower outage, the number of batteries required by the ONU-AP will increase. As the cost of the battery might vary depending on the location, therefore, we have considered the cost of one battery as ‘\$X.’ From Fig. 3.15, it is evident that as the efficiency of energy resource allocation increases (or the outage decreases), the number of batteries (or cost of the system) also increases. Further, it is obvious from Table 3.5 that for case I, as the allocation efficiency, i.e., outage increases from 5% to 10%, the cost decreases from \$59X to \$56X. Similarly, for case IV, a decrease in outage from 10% to 5% increases the cost by \$3X. Further, it can also be observed from Fig. 3.15 that the cost of case II is lower compared to case III. This is because the solar power in Jaipur is high compared to wind power, as can be observed from Figs. 3.6 and 3.8(b).

Table 3.6 summarizes the environmental and cost impact of the energy resource allocation scheme. It can be seen for all the three locations, case IV where batteries are installed with wind turbines and rotational PV panels has the least cost and emits the lowest CO₂ emission. This is because case IV has the least number of PV panels and batteries required to power ONU-AP. Moreover, the cost comparison at Benghazi for 40

Table 3.5: Trade-off analysis between allocation efficiency and cost for Jaipur at 40 Mbps

	Case I	Case II	Case III	Case IV
Outage (in %)	10%			
No. of batteries	56	39	49	32
Cost (in \$) (Assuming battery cost of \$X)	\$56X	\$39X	\$49X	\$32X
Outage (in %)	5%			
No. of batteries	59	42	51	35
Cost (in \$) (Assuming each battery cost \$X)	\$59X	\$42X	\$51X	\$35X

Table 3.6: Cost and environmental impact analysis for 40 Mbps throughput

	Cost Analysis (\$/W)				CO ₂ emissions (g/W)			
Location	Case I	Case II	Case III	Case IV	Case I	Case II	Case III	Case IV
Benghazi	15.98	14.11	8.24	7.38	4.22	3.72	2.69	2.46
Jaipur	16.48	15.12	14.26	13.43	4.36	3.99	3.87	3.64
Moscow	16.96	16.04	12.78	12.35	4.50	4.24	3.65	3.52

Mbps shows that a cost reduction of 48.43% is observed for case III compared to case I because of wind power supply. Similarly for case IV, a cost reduction of 53.81% is observed for Benghazi compared to case I because of wind and solar power profile. Furthermore, a CO₂ reduction of 11.84%, 36.25%, and 41.71% is observed at Benghazi for 40 Mbps throughput from case I to case II, III, and IV, respectively. While for Moscow cost reduces to 5.42%, 24.64%, 27.18% for case II, III, and IV compared to case I.

3.8 Conclusions

In this chapter, we proposed a joint energy resource optimization framework to allocate energy resources to power ONU-AP. A two-step iterative algorithm is employed to calculate the energy resources required by ONU-AP for the off-grid scenario based on the throughput profile and location of installation. Consequently, the joint energy resource allocation for different cases is analyzed, namely, a) Case I: batteries with fixed PV panels, b) Case II: batteries with rotational PV panels, c) Case III: batteries with fixed PV panels

and wind turbines, and d) Case IV: batteries with rotational PV panels and wind turbines. It is interesting to note that for a location like Benghazi, the number of batteries reduced from 42 to 24 with the introduction of wind power supply with fixed PV panels, whereas a reduction of 20 batteries and 6 PV panels is observed at 60 Mbps throughput with the introduction of wind turbine and rotational PV panels. Moreover, in order to validate the accuracy of the algorithm, an analytical framework is derived. The good agreement between the results of the analytical and iterative approach justifies the accuracy of the proposed framework. Furthermore, a socioeconomic analysis is presented to analyze the impact of energy resource allocation on CO₂ emissions and the cost of the system. For Benghazi at 40 Mbps throughput, a reduction in cost of 11.62%, 48.42%, and 53.79% is observed for case II, III, and IV, respectively compared to case I, whereas in terms of CO₂ emissions, a reduction of 11.89%, 36.33%, and 41.81% can be observed for case II, III and IV, respectively compared to case I. Moreover, the trade-off between energy resource allocation efficiency and cost is also analyzed in the chapter.

Chapter 4

Energy Resource Allocation for Green FiWi Network using Ensemble Learning

4.1 Introduction

The electricity generation from solar and wind panels is expected to cover about two-thirds of the renewable electricity market [118]. Moreover, every day typically has a different solar power profile. Thus, it's important to allocate energy resources so they aren't overused or underused. This chapter extends the work presented in Chapter 3 by utilizing ensemble learning for energy resource allocation in a green FiWi network. It is crucial to forecast the solar power at any given place in order to distribute the energy resources there. The dynamic nature of energy resource allocation based on daily solar power availability is not taken into consideration by the current resource allocation algorithms. To that end, we put forth a framework for allocating energy resources based on machine learning. Specifically, we employ random forest-based ensemble learning to estimate solar power.

4.2 Contributions

As the solar power profile generally differs for each day, thus energy resource allocation needs to be done such that the resources are neither under-utilized nor over-utilized. In order to allocate the energy resources at any specific location, it is essential to predict the solar power at that location. Consequently, this work extends the work proposed in Chapter 3 by utilizing a ML based joint energy resource allocation framework to allocate batteries and PV panels for an off-grid green FiWi network. A joint energy resource allocation problem is formulated to allocate the PV panels and batteries to operate ONU-AP. This work compares the proposed ML based energy resource allocation (*MERA*) approach with the traditional approach such as a) *Max* energy resource allocation, b) *Min* energy resource allocation, c) *Median* energy resource requirement, and d) Outage threshold based energy resource allocation.

4.3 Network Model

The ONU-AP is powered using PV panels, batteries, and wind turbines as evident from Fig. 4.1. It is assumed that the PV panels along with powering the ONU-APs are also responsible for charging the batteries. Specifically, the solar power (P_S) supplied to the ONU-AP is αP_S , where $0 \leq \alpha \leq 1$. Whereas the remaining fraction of solar power $(1 - \alpha)P_S$ is supplied to the batteries, so as to charge the batteries for operation during non-solar hours.

4.4 Solar Irradiance prediction using ML

This section focuses on predicting global horizontal irradiance (GHI). GHI is defined as the total solar radiation incident on a horizontal surface. This can be calculated by

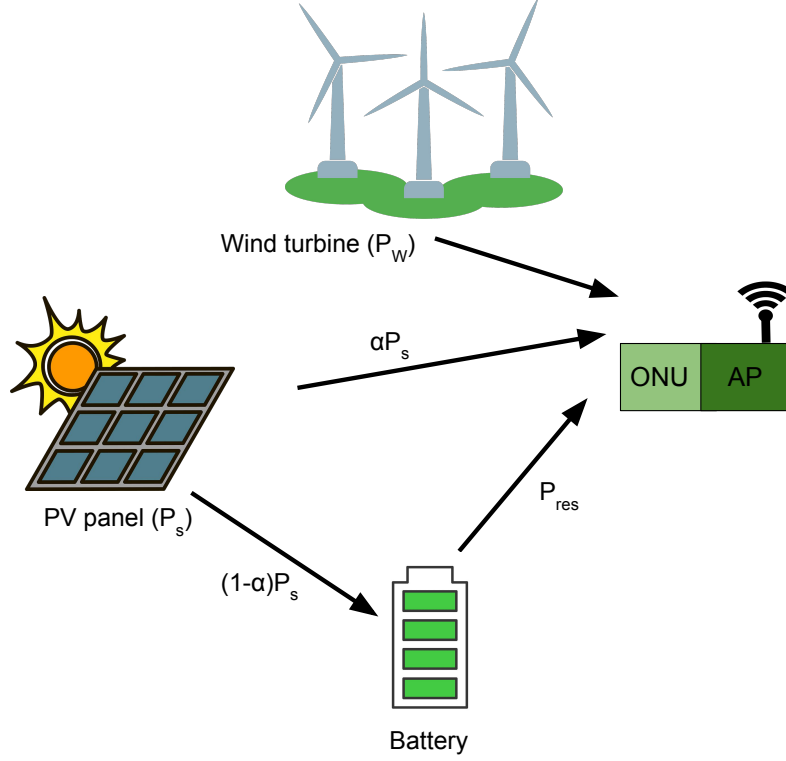


Figure 4.1: System model to supply power ONU-AP

using [119]:

$$I = D_N \cos(\theta^s) + D_H, \quad (4.1)$$

where D_N is direct normal irradiation (DNI) and is defined as the amount of solar radiation received per unit area by a surface that is held perpendicular (or normal) to the rays and D_H is direct horizontal irradiation (DHI), which represents solar radiation that does not arrive on the direct path from the sun, but has been scattered by clouds and particles in the atmosphere and comes equally from all directions and θ^s is the angle of incidence of the beam.

4.4.1 Building Model and Training

Ensemble learning is primarily used to improve the prediction. Therefore, we have used random forest regression-based ensemble learning, which uses multiple decision trees to

predict the output.

In random forest, each decision tree is built using a random sample of data points drawn without replacement [120]. Decision trees learn how to best split the dataset into smaller and smaller subsets to predict the target value [120]. For simulations, we have used classification and regression tree (CART) [121] algorithm as it supports numerical target variables or regressions. CART constructs binary trees using feature and a threshold that yields the largest information gain (IG) and minimum MSE at each node. The IG is defined as [122]

$$\text{IG}(X, Q_X) = H(X) - \sum_{v \in Q_X} \frac{|X_v|}{X} H(X_v), \quad (4.2)$$

where $H(X)$ is the entropy given by $\sum_i p(x_i) \log_2 p(x_i)$, where $p(x_i)$ is the probability of x_i and $\sum \frac{|X_v|}{X}$ is the ratio of the number of examples in the new set over the original set, X is the target variable or output, and Q_X represents the feature to be split. The goal is to minimize the MSE at each node as we go on increasing the depth of the tree. MSE is computed as follows [123]:

$$\text{MSE} = \frac{1}{N_s} \sum (x_a - x_p)^2, \quad (4.3)$$

where x_a is the actual value, x_p is the predicted value, and N_s denotes the total samples.

The structure of the random forest regressor is shown in Fig. 4.2, where the instance defines the value to be predicted. The mean of the output of all the decision trees gives the predicted value of the instance.

4.4.2 Data Set

In order to predict GHI for 2019, we use the data from 2001 to 2014 and 2017 to 2018 for New Delhi, India. After feature engineering, we used the following features of the data set: year, month, day, hour, temperature, dew point, DHI, DNI, GHI, relative humidity, solar zenith angle, pressure, precipitable water, wind speed [100].

For simulation, we segregated yearly data into 12 parts, one for each month of the

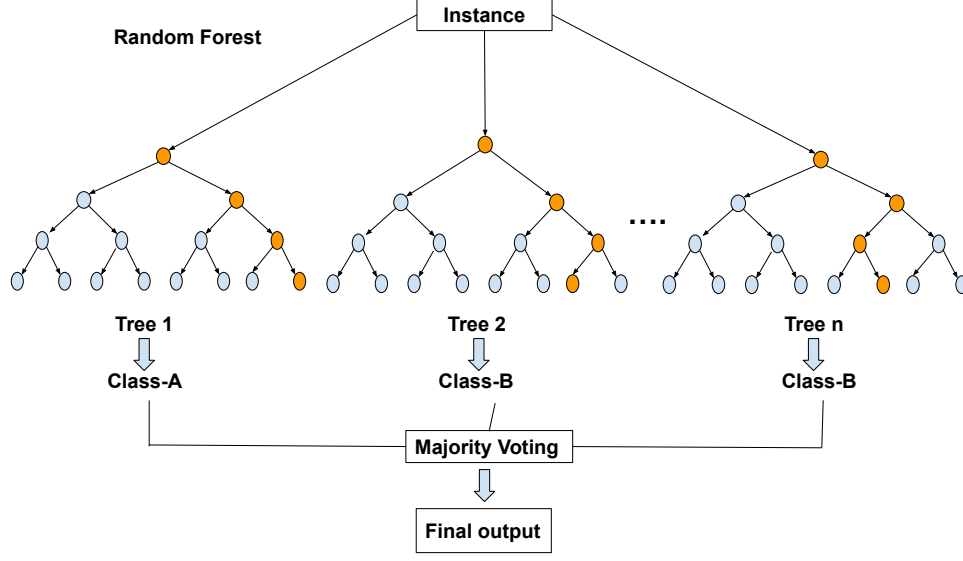
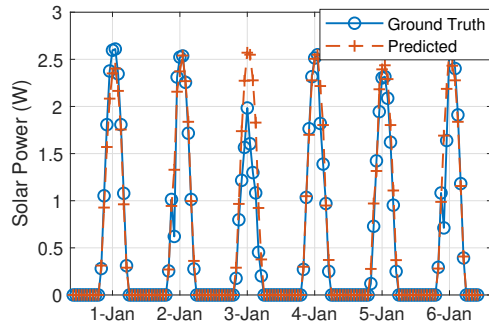


Figure 4.2: Random forest architecture

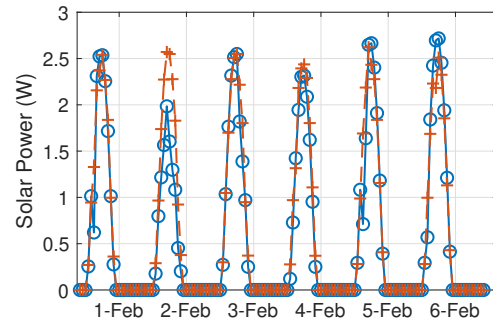
year. For each month, the model is trained with the same month of the prior years, i.e., from 2001-2014 and 2017-2018. For instance, if the data for Jan-2019 is to be predicted, the model is trained with January 2001-2014 and 2017-2018. Further, as the solar zenith angle has the maximum information gain of 0.482 hence, it is chosen as the first attribute for the split. Moreover, the number of estimators used in this work is 1000, i.e., there are 1000 trees in each forest, and the prediction value is calculated based on the mean of the outputs of these estimators. The predictions for New Delhi for the first six days of each month of 2019 can be seen in Fig. 4.3. It can be seen for each month the prediction is close to the actual values of solar irradiance.

4.4.3 Testing

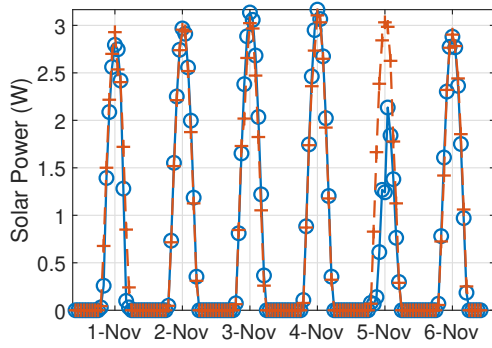
To evaluate the performance of solar irradiance prediction, we use the following performance metrics: a) R^2 score, b) RMSE, and c) %RMSE [123], [124].



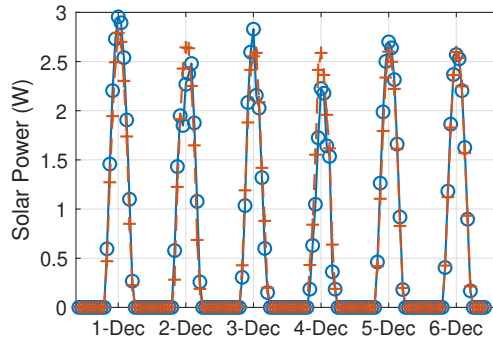
(a)



(b)



(c)



(d)

Figure 4.3: Actual vs. Predicted solar power profile for first six days of a) January, b) February, c) November, and d) December

4.4.3.1 R^2 score

R^2 score is a statistical measure in a regression model that determines the proportion of variance of the dependent variable, where the dependent variable is defined by an independent variable. In other words, R^2 shows how well the data fits into the regression model, i.e., the goodness of fit. R^2 is calculated as [124]:

$$R_{score}^2 = 1 - \left(\sum (x_a - x_p)^2 \right) / \left(\sum (x_a - x_{mean})^2 \right), \quad (4.4)$$

where x_a is ground truth, x_p is predicted value and x_{mean} is mean of all the actual values.

4.4.3.2 RMSE

Root Mean Squared Error is the measure of differences between values predicted by the model. In other words, it is standard deviation of the prediction errors and is calculated by [124]:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum (x_a - x_p)^2}. \quad (4.5)$$

4.4.3.3 %RMSE

It refers to the percentage RMSE and is calculated as [123]:

$$\% \text{RMSE} = \frac{\text{Calculated RMSE}}{\text{Maximum value of prediction}} \times 100. \quad (4.6)$$

4.5 Problem Formulation

In this section, a joint energy resource optimization problem to minimize the number of batteries as well as the number of PV panels required to operate ONU-AP is formulated. It is worthwhile to mention that the number of batteries depends on the number of PV panels and vice-versa. This is due to the fact that the power of the PV panels is required

to charge the batteries completely at T_H^{th} hour. Similarly, the number of batteries depends on the power required by ONU-AP during the non-solar hours. The optimization problem thus formulated is given as:

$$(P1) \quad \min_{Count_{PV}, Count_B, B_{CHG}^1} C_{PV} Count_{PV} + C_B Count_B, \quad (4.7)$$

$$s.t. \quad \beta P_B^{cap} \leq P_{SoC}^1(t) \leq P_B^{cap}, \quad \forall t \in [0, 23], \quad (4.8)$$

$$P_B^{cap} \leq P_{SoC}^1(T_H), \quad (4.9)$$

$$Count_{PV} P_S^1(t) + Count_B P_{SoC}^1(t) \geq P_{ONU-AP}(t), \quad \forall t \in [0, 23], \quad (4.10)$$

where $Count_{PV}$ and $Count_B$ is the number of PV panels and batteries, respectively, and $Count_{PV}, Count_B \in \mathbb{Z}$. C_{PV} and C_B is the cost of PV panels and batteries, respectively. P_B^{cap} is the battery capacity of the single battery, β is the depth of discharge value of the battery, $P_{SoC}^1(t)$ is the charge of a single battery at t^{th} hour, $P_S^1(t)$ is the power of a PV panel at t^{th} hour, and $P_{ONU-AP}(t)$ is the power consumption of ONU-AP at t^{th} hour. The solar power $P_S^1(t)$ is calculated from the irradiance profile calculated using ML-based prediction. The optimization problem (4.7) minimizes the cost of required number of PV panels and batteries, i.e., $C_{PV} Count_{PV}$ and $C_B Count_B$, respectively by finding the optimal values of number of PV panels ($Count_{PV}$) and number of batteries ($Count_B$). The constraint in (4.8) depicts that the charge of each battery at t^{th} hour, $P_{SoC}^1(t)$ does not exceed P_B^{cap} and does not discharge below the depth of discharge βP_B^{cap} , i.e., $P_B^{cap} \in [\beta P_B^{cap}, P_B^{cap}]$, $\forall t \in [0, 23]$. The second constraint in (4.9) denotes that the battery should be completely charged at the T_H^{th} hour. The power of ONU-AP should be fulfilled at each hour, i.e., the sum of power of the PV panel and batteries, $Count_{PV} \times P_S^1(t) + Count_B \times P_{SoC}^1(t)$ must fulfill the power requirement of ONU-AP, $P_{ONU-AP}(t) \forall t \in [0, 23]$.

It is evident from (4.7) that the objective function is a linear function of optimization variables $Count_{PV}$ and $Count_B$. However, the constraint in (4.10) is quadratic in na-

ture as it contains multiplication of two unknown variables $Count_B$ and $P_{SoC}^1(t)$. Hence, the optimization problem (P1) is a quadratic constraint linear programming problem (QCLP) [107]. The two sub-problems are solved using the PV panel allocation algorithm and the battery allocation algorithm, as shown in Chapter 3 with the solar power $P_S^1(t)$ calculated from the irradiance profile calculated using ML-based prediction.

4.6 Performance evaluation

In order to validate the performance of the proposed *MERA*, we compare the following approaches of energy resource allocation:

1. Maximum energy resource allocation (*Max* approach): In this approach, the energy resource allocation is calculated based on the worst solar power profile, i.e., lowest 24-hour solar power profile of the year.
2. Minimum energy resource allocation (*Min* approach): In this approach as discussed before, the energy resource allocation is calculated based on the best solar power profile, i.e., highest 24-hour solar power profile of the year.
3. Median energy resource allocation (*Median* approach): In this approach the energy resource allocation is calculated based on the median 24-hour solar power profile of the year, i.e., the median of all 365 days of the year.
4. Outage threshold based energy resource allocation: If the tolerable power outage limit set by the operator is $\Gamma\%$ outage per year then, based on the operator's outage limit, the energy resources required to operate ONU-AP is calculated. We have considered the outage threshold $\Gamma = 2\%$ which is the telecom standard outage limit [125].
5. Proposed ML based dynamic energy resource allocation (*MERA*): In this approach, dynamic energy resource allocation is done based on the solar power profile for each

day.

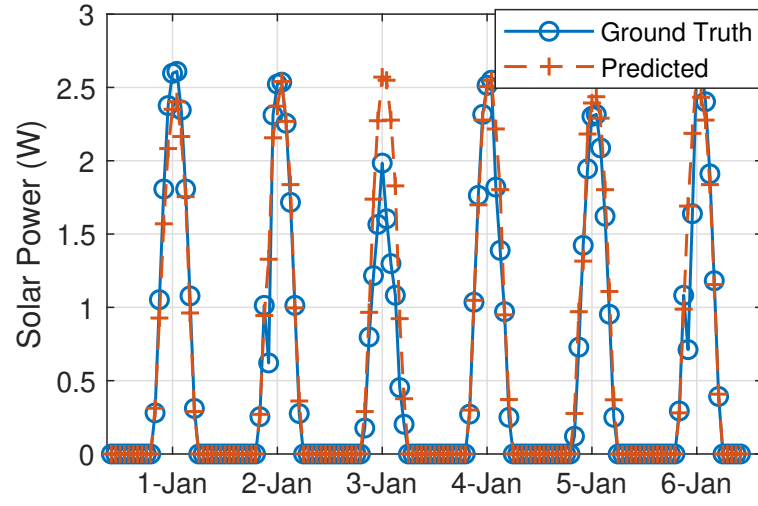
4.7 Results

The performance of the proposed joint energy resource allocation framework for the FiWi network is shown in this section. As mentioned before, in order to allocate the required number of batteries and PV panels to operate ONU-AP, a joint energy resource allocation is utilized. Further, the proposed approach is compared with the other approaches of energy resource optimization such as *Max*, *Min*, *Median*, and outage threshold approach, assuming both with wind and without wind scenarios. Moreover, the time at which the batteries are entirely charged is considered to be $T = 16:00$ hours. The DoD value for the battery, β , is considered 0.7 [113]. The capacity of the single PV panel and battery is considered to be 5W [111], [112].

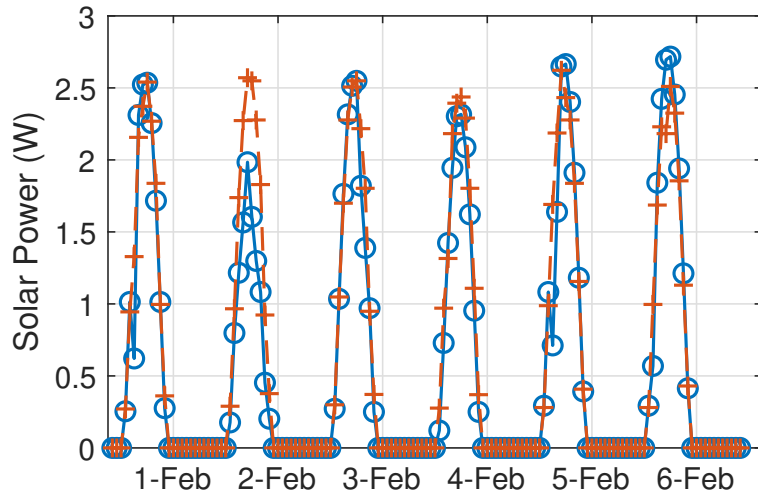
4.7.1 Efficiency of Machine Learning Predictions

The solar irradiance predictions for New Delhi for 2019 are analyzed in this section. Fig. 4.4 (of the revised thesis) shows the predictions of GHI for New Delhi for the first six days of January and February of 2019. It can be seen for each month the prediction is close to the actual values of solar irradiance. As mentioned before, in order to validate the predictions, we calculate R^2 score, RMSE, and % RMSE for the predicted solar irradiance values. The R^2 scores are presented in Table 4.2 (Table 4.1 of the revised thesis). It can be seen that the average R^2 score for the year is 84.375%. For October, the R^2 score is the highest, i.e., the prediction for October is the most accurate. However, for the months of July, August, and December, the prediction is least accurate as R^2 score is low¹. In order to find out whether the trend for these months is similar to other years, we predicted the

¹The reason for July, August, and December to have the lowest score might be due to the rainy season. The solar irradiance is unpredictable in the rainy weather, while this does not apply for the month of December as it is winter season in December in New Delhi.



(a)



(b)

Figure 4.4: Actual vs. Predicted solar power profile for New Delhi for first six days of a) January 2019 and b) February 2019.

solar irradiance for 2018 by using 2017's data as the testing set. The results for R^2 score for 2018 are summarized in Table 4.2. GHI predictions for July and August continued to be least accurate when predicting for the year 2018 by training on data before the year 2017, however, the model is able to predict GHI for the month of December as successfully as the other months [$R^2 = 94.00\%$] indicating that perhaps the month of December in 2019 is anomalous.

Table 4.1: R^2 scores for different months

Month	R^2 score	Month	R^2 score
January	91.00%	July	71.00%
February	83.15%	August	79.71%
March	86.53%	September	84.20%
April	93.24%	October	95.00%
May	93.96%	November	85.07%
June	84.64%	December	65.00%
Year		84.375%	

The RMSE values for different months of 2019 are shown in Table 4.3. It can be observed that RMSE for October is the lowest, i.e., 7.8%, which is also aligned with the R^2 score for October is the highest. Further, for December, the RMSE is the highest, i.e., 150.74. Moreover, the average %RMSE for 2019 is 10.23%.

Table 4.2: R^2 scores for different months of 2018

Month	R^2 score	Month	R^2 score
January	83.76%	July	77.57%
February	91.87%	August	82.81%
March	91.43%	September	73.19%
April	92.35%	October	96.28%
May	92.46%	November	95.18%
June	85.78%	December	94.00%
Year		84.375%	

Table 4.3: RMSE scores for different months of 2019

Month	RMSE	% RMSE	Month	RMSE	% RMSE
January	82.71	9.19	July	104.79	11.64
February	92.54	10.28	August	96.42	10.71
March	87.00	9.67	September	85.97	9.55
April	81.87	9.09	October	70.97	7.8
May	80.26	8.91	November	79.08	8.78
June	93.74	10.41	December	150.74	16.74
Year		92.17%		10.23%	

4.7.2 Energy Resource Allocation

In this subsection, we analyze the energy resources required to operate ONU-AP. The joint optimization problem ($P1$) is solved using an alternating approach, where the required number of batteries and PV panels are calculated alternatively until convergence. It may be noted that the proposed algorithm converges when the required number of batteries (or PV panels) at the current iteration and previous iteration are the same, i.e., $x(k+1) = x(k)$, where x is the number of batteries (or PV panels) and k is the number of iterations at which the algorithm converges. For iterative approach, the convergence happens at third iteration, where the number of batteries and PV panels converges as shown in Fig. 4.5. It is evident that for the first iteration, the number of PV panels and batteries are the highest, while as the number of iterations increases, the required number of batteries and PV panels converges. Fig. 4.6 shows the variation of the number of batteries and PV panels required to operate ONU-AP with the variation of α . It is evident that the energy resources required for without wind scenario are more compared to with wind scenario. This is due to the fact that with the addition of wind energy, the dependency of ONU-AP on PV panels and batteries reduces, therefore, the number of batteries and PV panels required are also lower. Moreover, as the number of batteries is dependent on the power consumption of ONU-AP during the non-solar hour, thus the number of batteries is not affected by change in α .

Furthermore, it can also be observed that as the fraction of solar power allocated

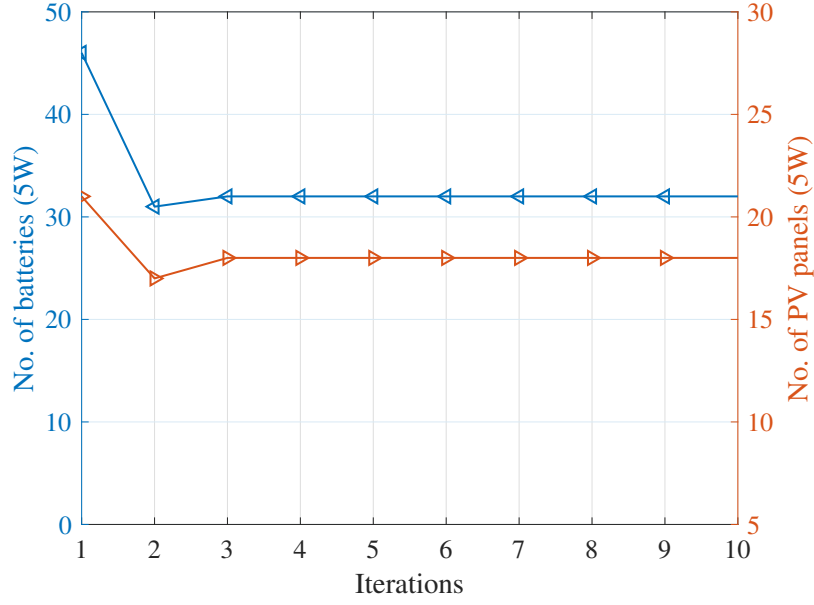


Figure 4.5: Convergence of the proposed approach for New Delhi for without wind scenario.

to ONU-AP increases, i.e., α increases, the number of PV panels required by ONU-AP decreases. Moreover, with the increase in α from 0.2 to 1, there is a reduction in the number of PV panels from 130 to 24 for without wind scenario. Similarly, there is a reduction in the number of PV panels from 120 to 22 for with wind scenario.

In Fig. 4.7, the PV panel allocation from 15-Mar-2019 to 24-Mar-2019 is shown. It is evident from Fig. 4.7(a) that as the solar power for 21th March is the least thus, the number of PV panels required by ONU-AP is the highest, i.e., 37 for without wind scenario and 29 for with wind scenario. Similarly, the solar power for 20th March is the highest; thus, the number of PV panels for this day is 19. If we use wind energy, then the number of PV panels reduces by 3. Further, it is observed that for with wind scenario the number of PV panels not only depends on the solar power but also depend on the wind power. Hence, the required number of PV panels is smaller for 15th March as compared to 20th March.

The amount of energy resources required by ONU-AP for different approaches is shown in Fig. 4.8. It is evident that with *Min* approach the energy resource allocated to ONU-AP

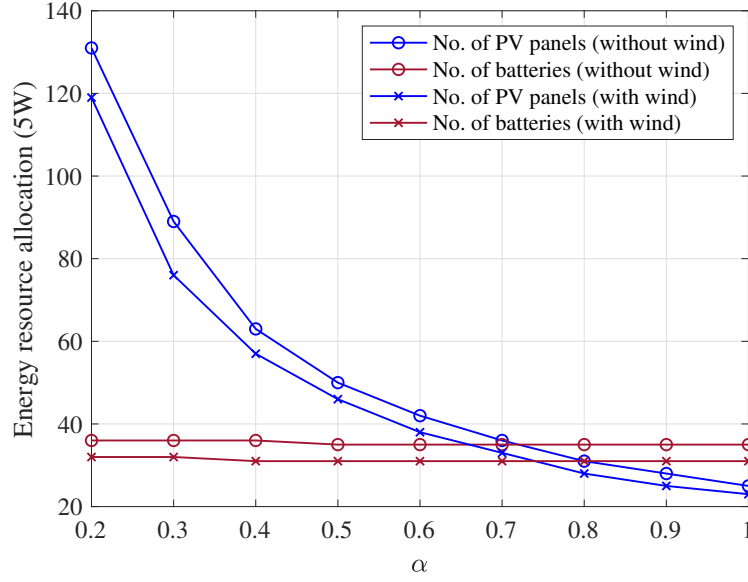
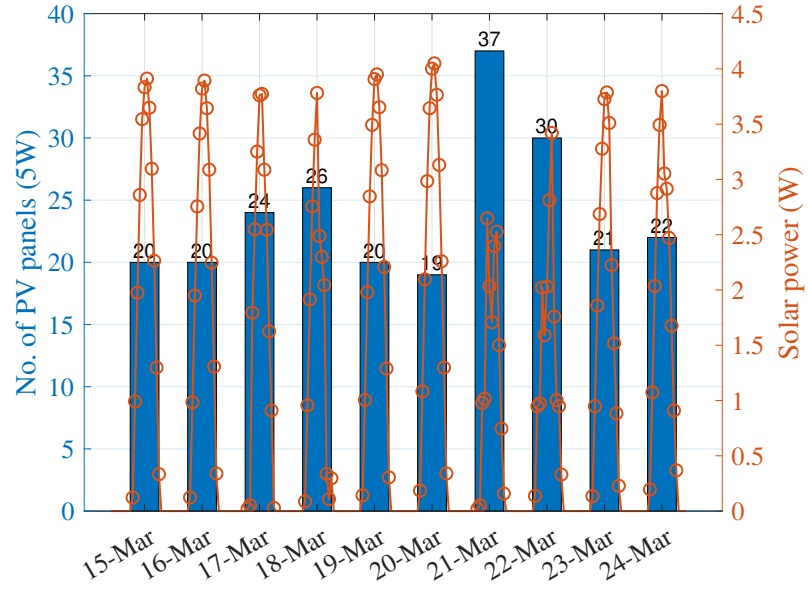


Figure 4.6: Energy resource allocation with variation of α

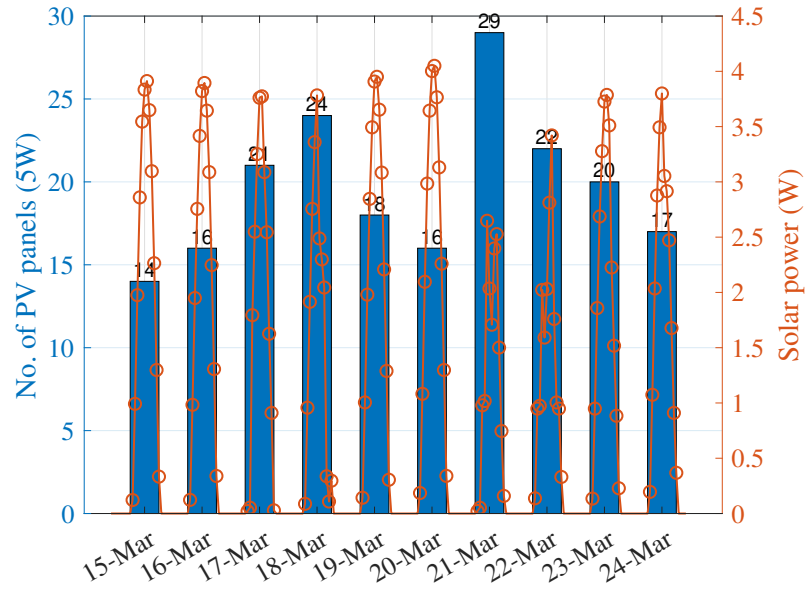
is lowest, while using *Max* approach the energy resource allocation is highest compared to other approaches followed by *MERA*, 2% outage, *Median* and *Min* approach. Further, it is evident that there is a reduction of 235 PV panels and 1 battery using *MERA* compared to *Max* approach. For simulations, we have used the value of α to be 1, as the resource allocation for $\alpha = 1$ is the lowest. However, this will affect the lifetime of the batteries, which is analyzed in detail in later subsection. In order to alleviate the effect of energy resource allocation on battery lifetime, operator may choose the value of α such that the desired battery lifetime can be guaranteed.

4.7.3 Battery Lifetime

The battery lifetime of a lead-acid battery is dependent on the number of charging-discharging cycles of the battery. The number of charging-discharging cycles is calculated using the rain-flow cycle counting algorithm [113]. A cycle-to-failure ratio (CTF_n) is specified by the operator based on the characteristics of the battery. The cycle-to-failure ratio represents the number of cycles the battery can have during its lifetime. The battery



(a) Without wind



(b) With wind

Figure 4.7: PV panel allocation according to solar profile.

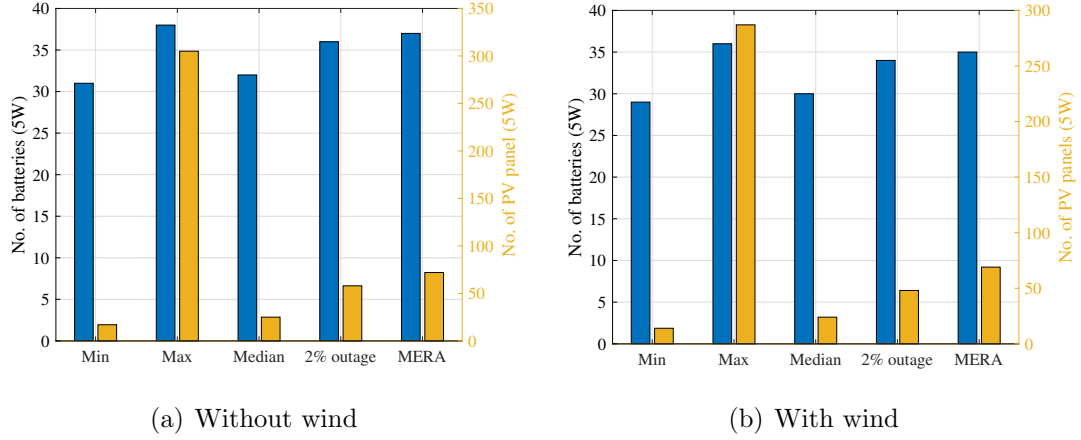


Figure 4.8: The number of batteries (blue bars) and PV panels (yellow bars) required by ONU-AP for i) Approach I: *Min* approach, ii) Approach II: *Max* approach, iii) Approach III: *Median* approach, iv) Approach IV: 2% outage approach, v) Approach III: Proposed *MERA*.

lifetime of a lead-acid battery can be calculated as follows [113]:

$$B_{lif} = \frac{1}{\sum_{n=1}^N \frac{C_n}{CTF_n}}, \quad (4.11)$$

where the number of cycles is denoted by C_n , CTF_n is the cycle-to-failure ratio, and the number of regions in which DoD is split is denoted by N .

Fig. 4.9 shows the lifetime and normalized cost analysis for the different approaches for with wind and without wind scenarios. The cost of wind turbine is calculated as:

$$C_W = C_{W_A} + C_{W_O}, \quad (4.12)$$

where C_{W_A} is the asset cost of the wind turbine and C_{W_O} is the O&M cost of the wind turbine [22]. The asset and O&M cost of PV panel, battery, and wind turbine are summarized in Table 4.4. The lifetime of a battery is considered to be five years, and the lifetime of the PV panel and wind turbine is considered to be 20 years [22]. Further, we have considered the system lifetime to be equal to the lifetime of PV panel, and therefore, the total number of replacements of battery is three. Finally, the cost of 5W PV panel,

Table 4.4: Cost of energy resources [22]

Parameter	Values
Asset cost of battery	\$195/kWh
Asset cost of PV panel	\$3000/kWh
Asset cost of wind turbine	\$2500/kWh
O&M cost of battery	2% of C_B^{asset}
O&M cost of PV panels	2% of C_{PV}^{asset}
O&M cost of wind turbine	2% of C_W^{asset}

battery and wind turbine are \$21.00, \$102.81, and \$17.60, respectively.

The normalized cost of the system is calculated with respect to the cost of without wind scenario for *Max* approach. It is evident from Fig. 4.9 that as the normalized cost increases, the lifetime of the batteries increases. This is due to the fact that as the normalized cost increases, the energy resource allocation at the backup ONU-AP increases. With the increase in the number of batteries and PV panels, the batteries will discharge to a higher discharging value. As an example, for the same ONU-AP load, if the energy resource allocation is low, i.e., the number of batteries and PV panels allocated to operate ONU-AP is low. Then, the batteries will go to a lower discharge value in order to provide the same amount of power. Similarly, if the energy resource allocation is high, the batteries will not go to a lower discharge value. Thus, it can be seen from Fig. 4.9a, the *Min* approach has the least energy resource allocation, and therefore, the lifetime of the batteries is the least. Similarly, the *Max* approach has the highest cost as well as lifetime also. Further, the cost of *MERA* approach decreases by 67% however, the lifetime of the batteries decreases by only 10% compared to the *Max* approach, which is an advantage of *MERA*. While in comparison with the *Min*, *Median*, and 2% outage approaches, the battery lifetime is higher for the proposed algorithm. A similar trend in the lifetime of the proposed approach is seen in Fig. 4.9b for the with wind scenario where the lifetime of batteries decreases by 12% with a decrease in 67% of the cost for *MERA* approach as compared to *Max* approach.

In Fig. 4.10, the lifetime of the batteries with respect to α is shown. It is evident

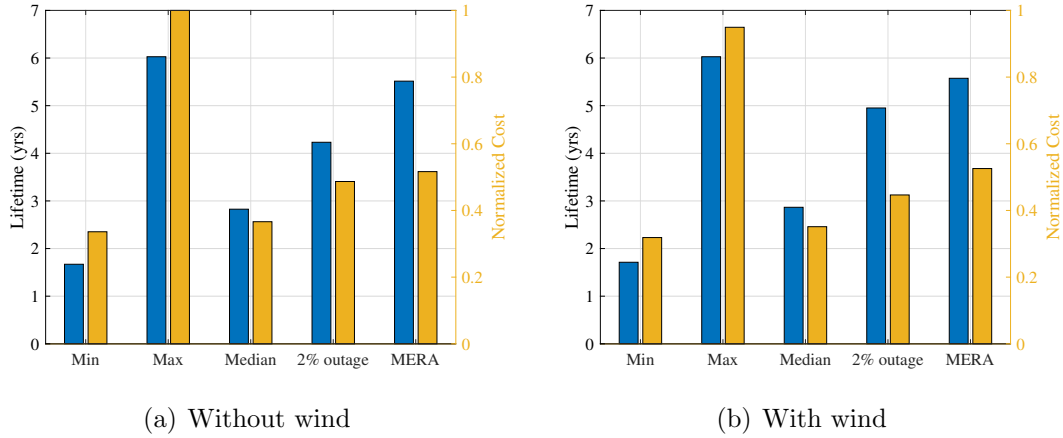


Figure 4.9: Battery lifetime (blue bars) and normalized cost (yellow bars) analysis for New Delhi at 40 Mbps throughput for i) Approach I: *Min* approach, ii) Approach II: *Max* approach, iii) Approach III: *Median* approach, iv) Approach IV: 2% outage approach, and v) Approach V: Proposed *MERA*.

that as α increases, the lifetime of the batteries decreases. This is because the energy resources allocated to ONU-AP decreases as α increases. As the allocated energy resources decreases, the batteries will have a lower state-of-charge or deep discharge. A battery of higher capacity might not discharge up to DoD limit, while a battery will lower capacity might have to go to deep discharge, and therefore, the lifetime of the battery decreases. Moreover, for *MERA* with 2% outage there is a further decrease in the energy resource allocation compared to *MERA* with 0% outage therefore, the lifetime of the batteries further decreases by 1 year 4 months for $\alpha = 1$.

4.7.4 Power Outage Analysis

This subsection analyzes the performance of the energy resource allocation framework in terms of power outage. The power outage in the system represents the amount of time (in %) for which the power supply to the ONU-AP is unavailable. It is evident from Fig. 4.11 that the outage for *MERA* approach is the least, while for *Min* approach the outage is maximum. Further, it is evident that for *Min*, *Max*, *Median*, and 2% outage approach, the outage is inversely proportional to the normalized cost. As the normalized cost increases,

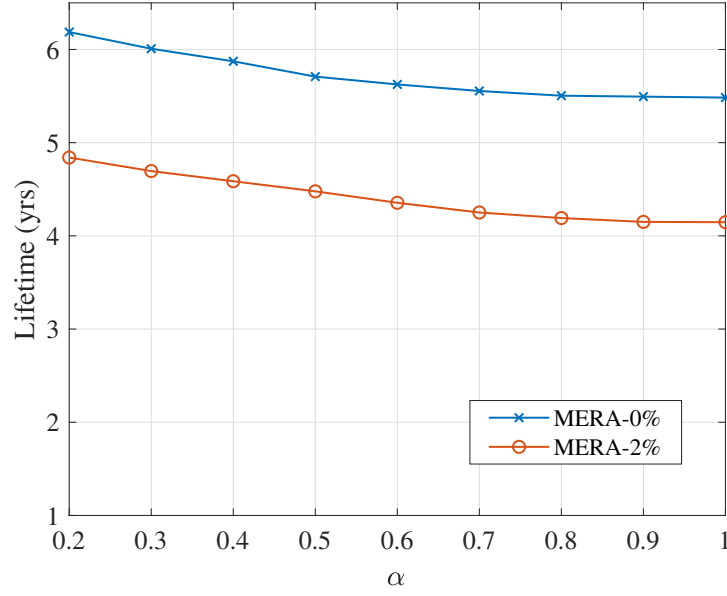


Figure 4.10: Battery lifetime variation with respect to α

the outage decreases. This is due to the fact that as the normalized cost increases, the energy resource allocation also increases, thus the probability that power will not be available to ONU-AP is less and the outage will decrease. Moreover, the advantage of the proposed *MERA* in terms of outage is clearly evident from Fig. 4.11a. The outage for *MERA* is 0% which 0.5% less than the outage from *Max* approach, whereas in terms of cost a reduction of 67% is achieved. A similar trend is achieved for with wind scenario in Fig. 4.11b, where the outage for proposed *MERA* is the least. Further, it can be seen from Fig. 4.11 there are only three approaches providing outage less than the considered operator's power outage threshold of 2%. These three approaches are compared with the proposed *MERA* with 2% outage in Fig. 4.12 for without and with wind scenario. It is evident that *MERA* with 2% outage has a lower energy resource requirement compared to the other three approaches. If we compare two approaches with equal outage, i.e., *MERA* with 2% outage and 2% outage with non-ML based energy resource allocation, it is evident that using *MERA* the energy resource requirement is less. Moreover, there is a trade-off between *MERA* with 2% and *MERA* with 0% outage, i.e., as normalized cost

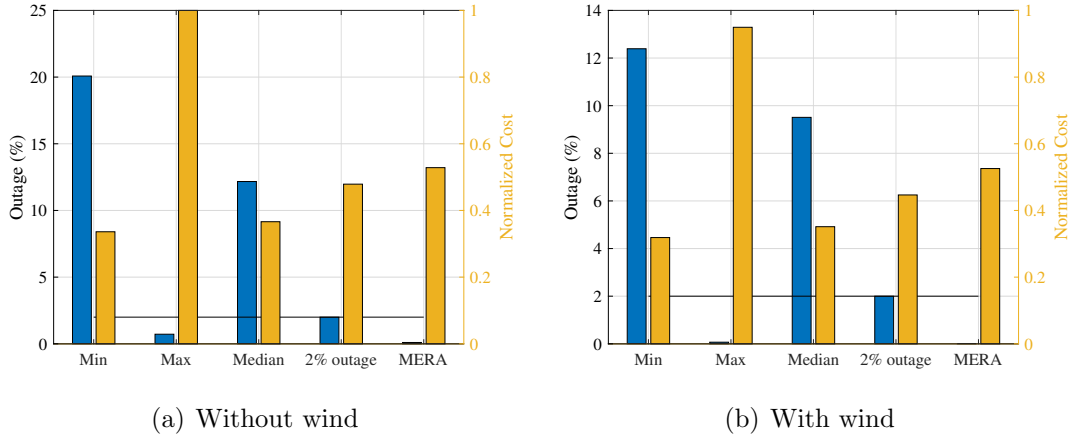


Figure 4.11: Power outage (blue bars) and normalized cost (yellow bars) analysis for New Delhi at 40 Mbps throughput for i) Approach I: *Min* approach, ii) Approach II: *Max* approach, iii) Approach III: *Median* approach, iv) Approach IV: 2% outage approach, and v) Approach V: Proposed *MERA*.

increases, the outage decreases.

4.7.5 Carbon Footprint Analysis

The environmental impact of the energy resource allocation scheme in terms of CO₂ emissions is shown in Fig. 4.13. The CO₂ emissions for battery, wind turbine, and PV panel are 4.22, 0.96, and 0.96 tonnes CO₂/MWh, respectively [24]. For 2017-18, the weighted average CO₂ emission for India is 0.82 tCO₂/MWh [115]. It can be observed from Fig. 4.13 that the CO₂ emissions for FiWi network are proportional to the allocated energy resources. This is due to the fact that as the amount of energy resource increases, the cost and CO₂ emissions from the energy resources increases. Further, it is evident from Fig. 4.13 that CO₂ emissions as well as cost is the least for *MERA* with 2% outage, which is 63% and 73% lesser than the grid power supply for without and with wind scenario, respectively.

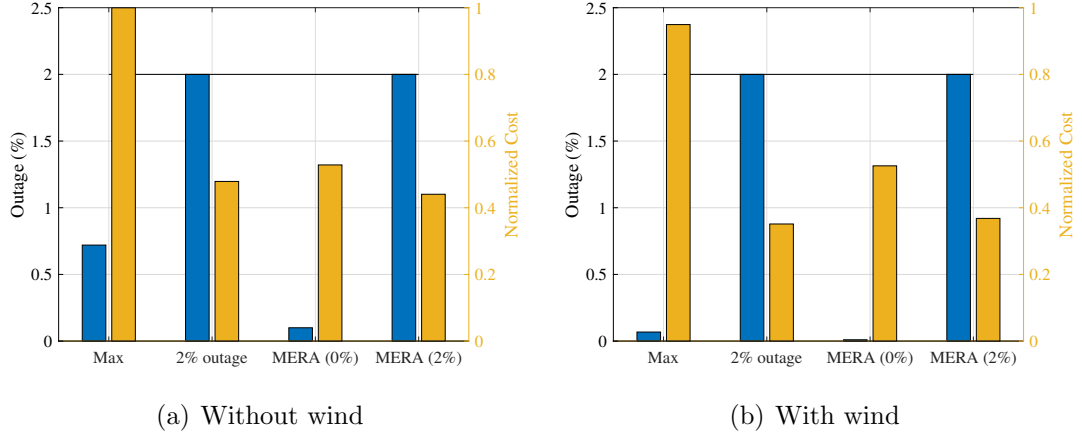


Figure 4.12: Power outage (blue bars) and normalized cost (yellow bars) analysis for New Delhi at 40 Mbps throughput for the cases where outage is below the outage threshold of 2%, i.e., i) Approach I: *Max* approach, ii) Approach II: 2% outage approach, iii) Approach III: Proposed *MERA* with 0% outage and v) Approach IV: Proposed *MERA* allocation with 2% outage.

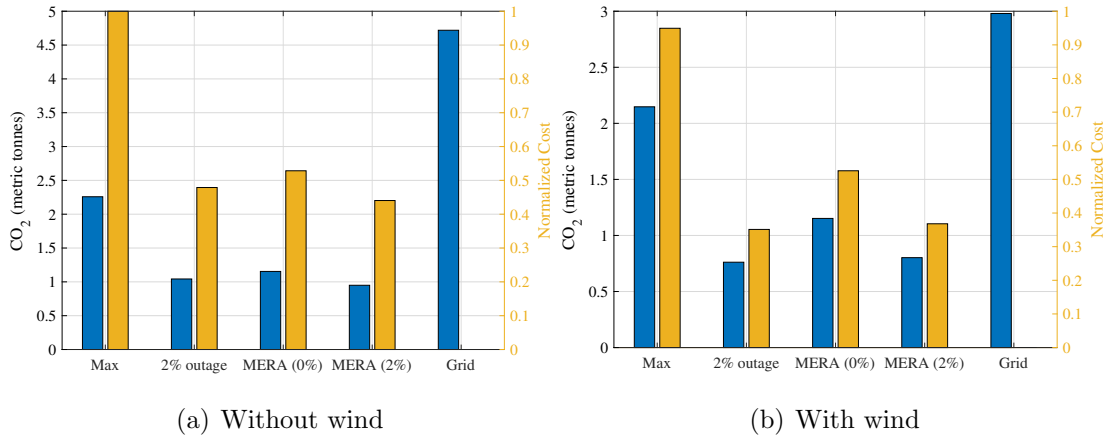


Figure 4.13: CO₂ emissions (blue bars) and normalized cost (yellow bars) analysis for New Delhi at 40 Mbps throughput for i) Approach I: *Max* approach, ii) Approach II: 2% outage approach, iii) Approach III: Proposed *MERA* with 0% outage and v) Approach IV: Proposed *MERA* allocation with 2% outage.

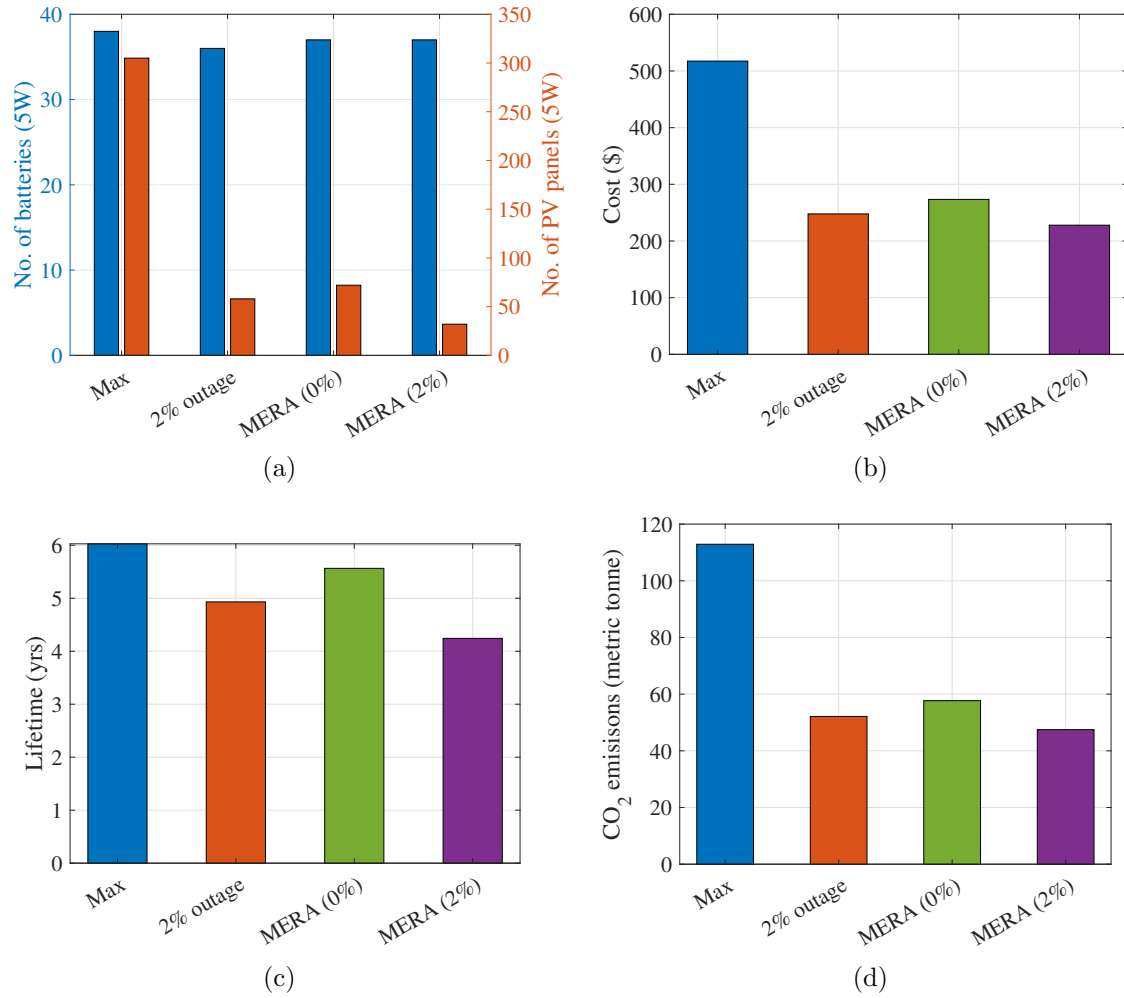


Figure 4.14: Analysis for (a) Energy resource allocation, (b) Cost, (c) Lifetime, and (d) CO₂ emissions for different approaches for without wind scenario.

4.7.6 Trade-Off Analysis Between Energy Resource Allocation, Battery Lifetime, Power Outage, Cost, And CO₂ Emissions

The trade-off between energy resource allocation, battery lifetime, power outage, cost, and CO₂ emissions is shown in Fig. 4.14. In comparison with *Max* energy resource allocation, i.e., the best case scenario, there is a reduction of 235 PV panels and 2 batteries compared to *MERA* with 0% outage. Similarly, a reduction in cost of \$200, 0.5% outage, and 47.82% CO₂ emissions is evident for *MERA* with 0% outage compared to *Max* approach. However, there is a decrease in lifetime by 6 months compared to *Max* approach. Thus, a trade off between lifetime and energy resource allocation is clearly evident from Fig. 4.14. Further, in comparison with ML based 2% outage scheme, the energy resource requirement of *MERA* with 0% outage increases by 10%, however, the lifetime of the batteries decreases by 18% with a decrease in outage of 2%. Furthermore, for the same outage of 2%, the advantage of *MERA* compared to non-ML based 2% outage scheme is evident in terms of reduction in the number of PV panels by 30, the number of batteries by 1, 21.47% cost, and 18.64% CO₂ emissions. However, as there is a trade-off between lifetime and energy resource allocation, thus, with the use of *MERA* there is a reduction in lifetime of batteries by 6 months (10%). However, it can be noted that with the reduction in lifetime by 10%, there is an improvement in CO₂ emissions and cost by 21.47% and 18.64%, respectively. Thus, it can be concluded that using *MERA* the performance of the system is improved.

4.8 Conclusions

In this chapter, we proposed a joint energy resource optimization framework to minimize the batteries and PV panels required to operate ONU-AP for a FiWi network. We divided the optimization problem into two sub-problems: 1) Minimum PV panel allocation for a

fixed number of batteries (*MinBatAlloc*) and 2) Minimum battery allocation for a fixed number of PV panels (*MinPVAlloc*). These two sub-problems are then solved alternatively to calculate the energy resources required by ONU-AP for with and without wind scenarios. Further, in order to classify the fraction of solar power supplied to operate ONU-AP and battery, we introduced a system parameter α and analyzed its impact on system performance, such as energy resource allocation and lifetime. Moreover, we compared the performance of our proposed approach *MERA* with the non-ML-based approaches, such as *Max*, *Min*, *Median*, and outage threshold. The results showed that using *MERA*, there is a reduction in energy resource allocation, cost, CO₂ emissions, as well as outage compared to *Max* energy resource allocation, which is the best case scenario. However, in comparison to *Max* resource allocation, there is a reduction of battery lifetime by 10%. Thus, a trade-off between energy resource allocation and lifetime has been shown in this chapter. Moreover, for the same outage limit of 2%, the proposed *MERA* has a reduction in 18.64% CO₂ emissions, 21.47% cost, 30 PV panels, and 1 battery in comparison of *MERA* with 0% outage. However, due to the reduction in energy resources, there is a decrease in battery lifetime of 10% for *MERA* with 0% outage compared to *MERA* with 2% outage.

Part II

QoS Aware High Throughput FiWi Networks

Chapter 5

QoS Analysis for High Throughput FiWi Network

5.1 Introduction

One of the critical components while proposing energy resource allocation strategies, as mentioned in Chapters 3 and 4, is maintaining the QoS requirement of the users. This chapter utilizes deficit DBA for enabling QoS in an integrated XG-PON with an IEEE 802.11ac-based WLAN network. Deficit DBA makes effective use of channel bandwidth and allocates the unused bandwidth of the higher prioritized services to low priority service T-CONTs dynamically.

5.2 Contributions

This work considers the integration of XG-PON with IEEE 802.11ac based WLAN network using deficit DBA at OLT. Each user is assumed to transmit three kinds of traffics, i.e., voice (VO), video (VI), and BE. The voice traffic is given the highest priority, followed by video and best effort. The aggregated traffic from each user is 100 Mbps. Deficit DBA makes effective use of channel bandwidth and allocates the unused bandwidth of the higher prioritized services to low priority service T-CONTs dynamically. In order to incorporate the real-time burst nature of the traffic, we use the Poisson Pareto Burst Process (PPBP) to model the upcoming traffic from the users.

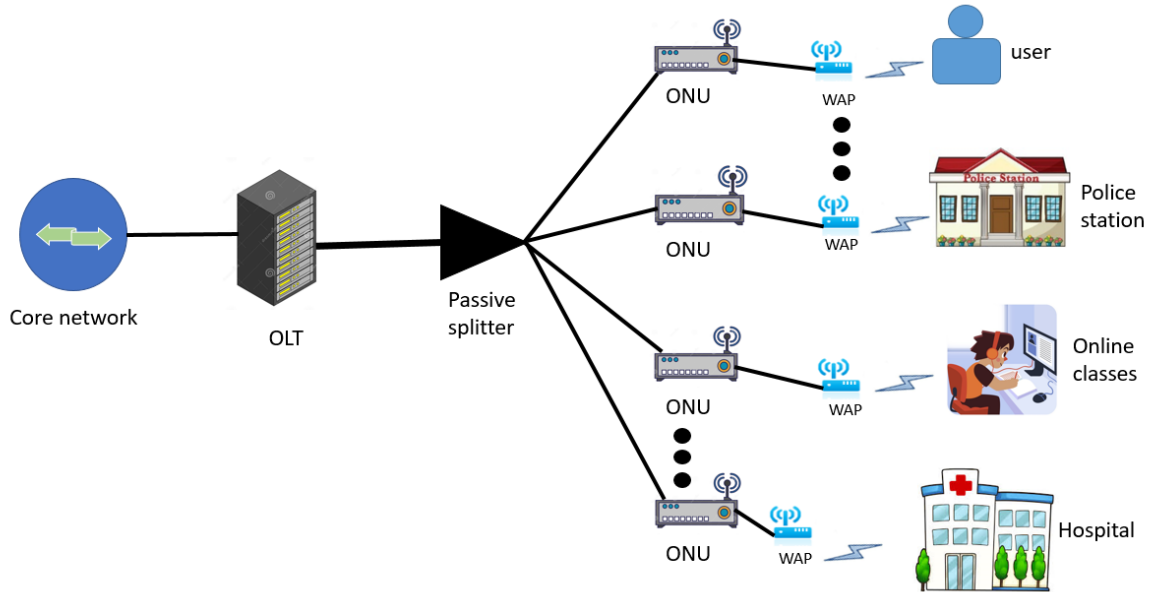


Figure 5.1: System architecture for the considered FiWi network.

5.3 System Description

Fig. 5.1 shows the system architecture for the considered FiWi network. The DBA is very crucial to avoid collision of packets sent by multiple ONUs. The deficit DBA is applied to allow each T-CONT to use the shared medium by assigning sufficient bandwidth to maximize the bandwidth utilization. In [50], the authors compared the performance of deficit DBA with the existing X-GIANT algorithm. The authors concluded that with the use of deficit DBA, they were able to improve performance in terms of the average latency and fairness index of the FiWi network.

Algorithm 4 illustrates the bandwidth allocation to each T-CONT using deficit DBA. It can be observed that after serving the users with voice and video traffic i.e., users in T-CONT 2 and T-CONT 3, the remaining bandwidth is used to serve the unserved users of T-CONT 4. Table 5.1 briefs about the type of bandwidth allocated to each T-CONT type and the corresponding served AC in the deficit DBA algorithm [48].

Algorithm 4 The deficit DBA algorithm

Inputs: $AB_{\min}$: Minimum allocation bytesRequired- BW : Bandwidth required by the users. FB : Number of bytes in a frame. $AB_{\max}$: Maximum allocation bytes N_2 : Number of users with voice traffic. N_3 : Number of users with video traffic. N_4 : Number of users with BE traffic. λ_{NS} : Assured:Non-assured bandwidth for T-CONT 3. $\bar{\lambda}_{NS}$: $1 - \lambda_{NS}$. $XG - PON_{upstream}$: upstream bandwidth of XG-PON 2.488 Gbps. $r_{traffic}$: Incoming traffic for voice:video:BE.Remaining- BW : Remaining BW after granting bandwidth to voice and video traffic.Threshold- BW : Threshold bandwidth, Remaining- BW / N_4 .

Grant-size: Granted bandwidth.

Total Deficit- BW : total deficit bandwidth.Deficit- BW : Deficit bandwidth.

- 1: **T-CONT 1**: Grants 128 kbps of fixed bandwidth.
 - 2: **T-CONT 2**: Grants bandwidth $BW_{T-CONT2}$ = minimum of {Required- BW , $AB_{\min}$, FB }.
 - 2: **T-CONT 3**: Grants bandwidth $BW_{T-CONT3}$ = minimum of {Required- BW , $AB_{\max}$ }
 - For assured round, $AB_{\max} = (\text{Unused-}BW_{T-CONT2} + \lambda_{NS} \times r_{traffic} \times XG - PON_{upstream}) / N_3$ corresponding to each T-CONT 3 user.
 - For non-assured round, $AB_{\max} = (\text{Unused-}BW_{T-CONT2} + \bar{\lambda}_{NS} r_{traffic} XG - PON_{upstream}) / N_3$ for each of T-CONT 3 user.
 - Go to Step 4.
 - 3: **T-CONT 4**:
 - Deficit- BW = Threshold- BW - Required- BW .
 - Total Deficit- BW = Total Deficit- BW + Deficit- BW
 - 4: **if** Deficit- $BW > 0$ **then**
 - 5: Threshold- BW = [Remaining- BW + Total Deficit- BW] / N_4 Grant-size = minimum of {Required- BW , Threshold- BW }
 - 6: **end if**
-

Table 5.1: Deficit DBA bandwidth allocation

T-CONT	Bandwidth type	Guaranteed data rate (GDR) [‘]	Surplus data rate (SDR)
T-CONT 1	Fixed bandwidth	128 Kbps	-
T-CONT 2	Assured bandwidth	GDR_2/N_2	$(MDR_2 - GDR_2)/N_2$
T-CONT 3	Non-assured & assured bandwidth	GDR_3/N_3	$(MDR_3 - GDR_3)/N_3$
T-CONT 4	Best effort bandwidth	$BW_{remaining}/N_4$	-

It can be seen that fixed bandwidth is allocated to T-CONT 1 of 128 kilo bits per second (Kbps). T-CONT 2 and 3 are reserved for voice and video traffic, respectively. The guaranteed bandwidth allocated to T-CONT 2 and 3 depends on the GDR and the number of users generating voice and video traffic, i.e., N_2 and N_3 , respectively. The surplus bandwidth assigned to T-CONT 2 and 3 depends on the maximum data rate for the voice and video traffic, i.e., MDR_2 and MDR_3 , respectively. The bandwidth allocated to T-CONT 3 is further divided into non-assured and assured bandwidth. Assured bandwidth is allocated to real-time services such as real-time video streaming, while non-assure bandwidth is allocated to non-real-time videos such as downloadable video. The bandwidth remaining (Remaining- BW) after serving T-CONT 2 and 3 is allocated to BE traffic according to the number of users sending BE traffic, i.e., N_4 .

5.4 Simulation Environment

The standards-compliant converged system using pre-existing XG-PON and EDCA-based WiFi network is implemented in NS-3. The XG-PON network is composed of an OLT connected with 16 ONUs via splitter and shared optical cable, and ONUs are connected via ethernet links to some APs that have a varied number of WiFi clients on the WLAN side. Each WLAN has a bandwidth of 180 Mbps. Each T-CONT's queue size is taken as 1 MB [47]. There is a propagation latency between OLT and ONU of 0.4 ms that represents 60 km distance. As per the upstream global traffic scenario specified in Table 2.3, the

majority of BE traffic is generated, followed by video and then voice, considering the parameters mentioned in Table 2.3. In order to properly design and analyze the performance of converged XG-PON and WiFi networks, we need to clearly understand the nature of network traffic that is being generated from WiFi clients.

The PPBP traffic model used for generating BE and video traffic characteristics satisfies pivotal statistical properties of real-life IP networks. It enables ease of use and is computationally efficient to allow scalable scenarios [126]. The incoming traffic has a characteristic burst length that is present on a wide range of time scales and is effectively captured in the PPBP traffic model. It can be statistically interpreted by the principle of self-similarity, and it exhibits long-range dependence [127]. The auto-correlation function of such a self-similar process follows power law latency, which is much slower than exponential latency. The degree of the time series of a self-similar model is expressed by the Hurst parameter (H). It expresses the speed of decay of the series auto-correlation function, and for long-range dependence (LRD), its value varies from $1/2 < H < 1$. As it approaches 1, the degree of both self-similarity and LRD increases. Regarding PPBP modelling, bursts arrive according to poisson process with rate λ_P and the burst length follows Pareto distribution given by H parameter. Each burst flow has a constant bit rate (CBR) r_b [128]. A number of wireless stations generating voice, video, and BE traffic is taken in such a way that approximately 5-8%, 25-30%, and 65-70% are voice, video, and BE traffic, respectively. Each wireless station would operate only one application at a given instant of time. Each wireless station is connected to a single WAP, which in turn links to a specific ONU.

For the simulation of FiWi network architecture, we used pre-existing XG-PON and IEEE 802.11ac wireless network features in NS-3 software. The FiWi network consists of 4 ONUs, and each ONU is connected to a WiFi access point (WAP) to receive WiFi packets from the clients. The ONUs are served by a single OLT via a passive splitter. The distance between ONU and OLT is considered to be 60 km. The queue size for each

T-CONT is taken as 1 MB [47]. For the integrated network, we have used point-to-point protocol]. We used IEEE 802.11ac-based WLAN with the maximum bandwidth of the channel being 160 MHz. For the wireless network, a 4×4 MIMO system is considered. Table 5.2 shows the incoming traffic parameters for a user. It can be observed from Table 5.2 that the sum of traffic coming from the users is more than 100 Mbps, thus, through extensive simulations, we are able to provide a data rate of 100 Mbps to each users.

Table 5.2: Incoming Traffic Parameters

AC	Data Packet Size	Encoding bit rate	Traffic Model
Voice	160 Bytes	5 Mbps	ON-OFF model with ON duration is exponential with a mean of 0.35s and OFF duration is exponential with mean of 0.65s
Video	795 Bytes	40 Mbps	PPBP with hurst parameter, $H=0.9$
BE	1472 Bytes	64 Mbps	PPBP with hurst parameter, $H=0.5$

5.5 Performance Evaluation

In this section, the performance of the considered FiWi network is presented.

Fig. 5.2 shows the variation of end-to-end latency for T-CONT 2 (voice), T-CONT 3 (video), and T-CONT 4 (BE). It can be observed that the end-to-end latency for the integrated FiWi network increases as the network load increases. Further, for voice traffic, the end-to-end latency is the least, while for BE traffic, the end-to-end latency is the highest. Moreover, it could also be observed that for low traffic load, the end-to-end latency performance for voice, video, and BE is similar, but as the traffic load increases, the end-to-end latency performance varies according to the priorities of the ACs. Similarly, BE traffic has the least priority and the end-to-end latency for BE is the highest. A similar trend for PLR is observed in Fig. 5.3. Further, it can also be observed that for voice, the

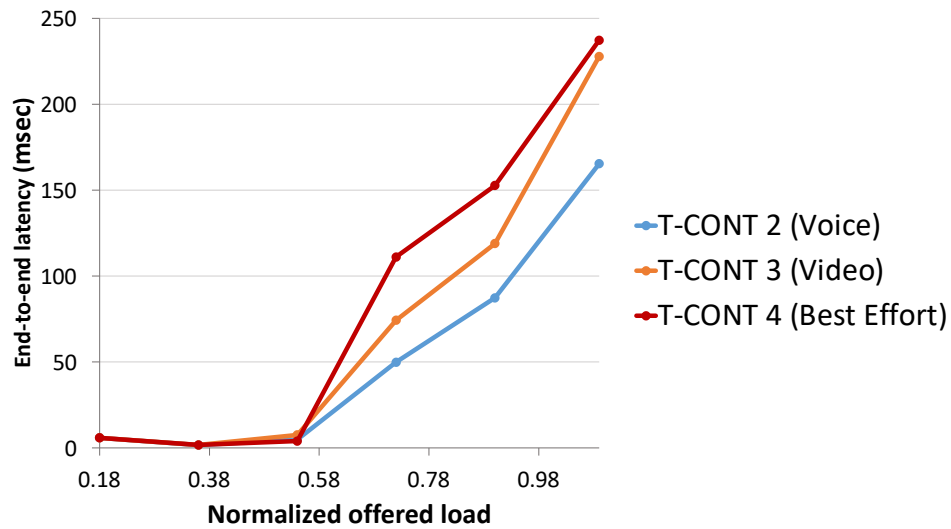


Figure 5.2: End-to-end latency using deficit DBA algorithm.

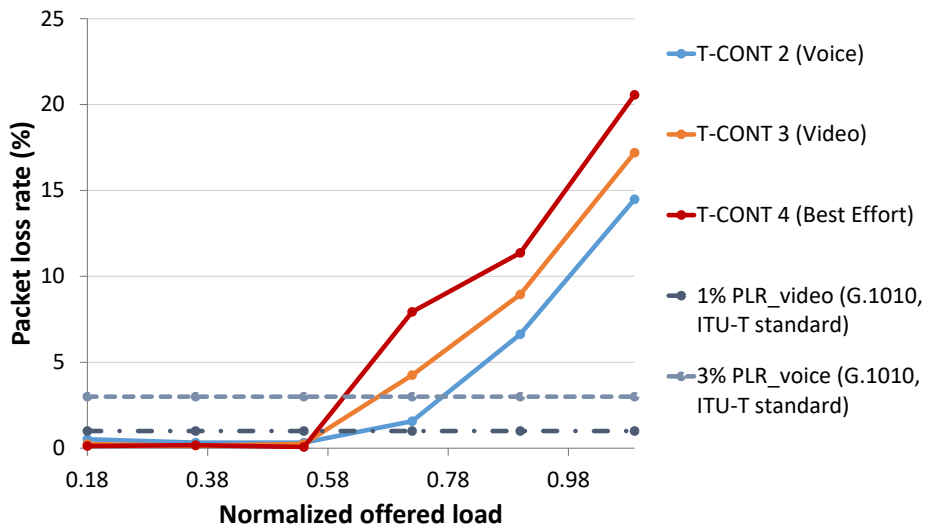


Figure 5.3: Packet loss rate using deficit DBA algorithm

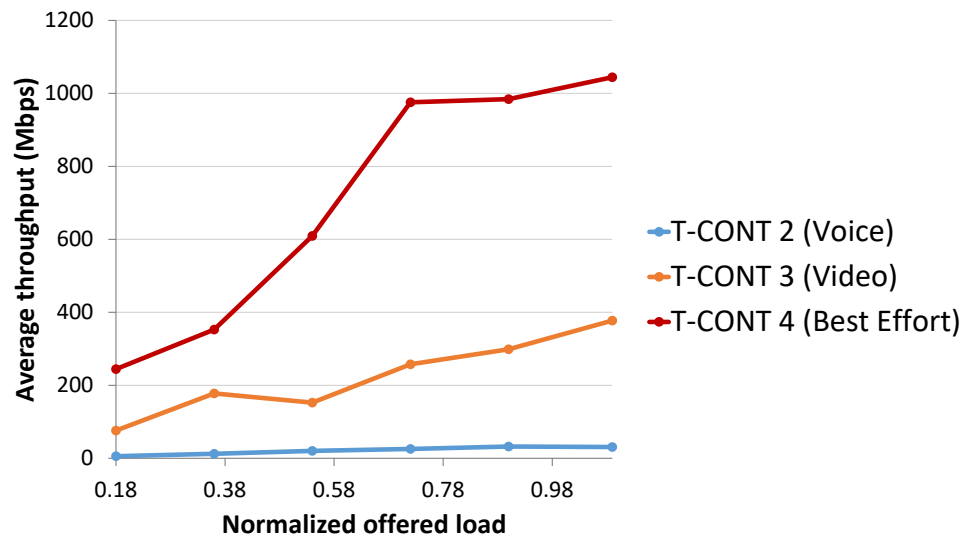


Figure 5.4: Average throughput using deficit DBA algorithm.

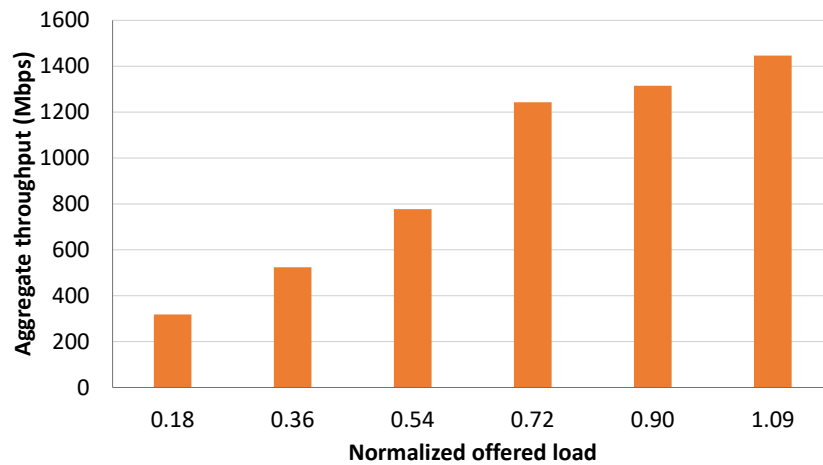


Figure 5.5: Aggregate throughput using deficit DBA algorithm

PLR is in the acceptable range of ITU-T standard up to a network load of 80%. Also, for video traffic, the network performance is within the acceptable range of ITU-T standard for 60% network load. Fig. 5.4 shows the variation of average throughput for voice, video, and BE. It can be observed that the throughput of the network increases as the network load increases. Further, it can be observed that for BE traffic, the throughput increases as the network load increases to 92%. As the network load increases beyond 92%, there is no significant change in the throughput of the network. Although, for voice and video traffic a significant change can be seen. This is because voice and video traffic have higher priority over BE traffic. Similarly, from Fig. 5.5 it can be observed that for a fully loaded network, we are able to achieve an aggregate throughput of around 1.5 Gbps, which is 62.5% of $XG - PON_{upstream}$.

5.6 Conclusions

In this chapter, we utilized the deficit DBA algorithm to enhance the throughput of the FiWi network. Specifically, we are able to achieve a throughput of 100 Mbps per user for an integrated network. The use of high-end wireless standards such as IEEE 802.11ac-based WLAN helps in achieving the QoS parameters within the tolerable range of ITU-T standards. The simulation results show the performance of the FiWi network for end-to-end latency, average throughput, PLR, and aggregate throughput. The results demonstrate that for voice, we are able to achieve the PLR within a tolerable range of ITU standards for a network load of 80%, and for video, the PLR is maintained within a tolerable range for a network load of up to 60%. Moreover, the results demonstrate that for a fully loaded network, we are able to achieve an aggregate throughput of 62.5% of the XG-PON upstream capacity.

Part III

Energy Resource Allocation for Green FiWi Networks

Chapter 6

Traffic Prediction Assisted Wavelength Allocation in Vehicle-to-Infrastructure Communication: A Fiber-Wireless Network Based Framework

6.1 Introduction

In order to meet the demand for high throughput vehicular networks with high reliability and low delay, mobile edge computing has emerged as one of the possible solutions [14], [15]. However, single communication technology cannot meet the ever-changing wireless communication requirements in highly dynamic vehicular networks [15]. One of the most common solutions to improve the QoS requirement and incorporate the diversity of vehicular network traffic is the coexistence of multiple communication technologies [15]. This chapter extends the work presented in Chapter 5 to dynamic vehicular network traffic. As vehicular network traffic is more critical and requires high safety and security, maintaining QoS in vehicular network traffic becomes essential. Additionally, this chapter utilized traffic prediction to assist wavelength allocation in V2I communication.

6.2 Contributions

In this work, we intend to improve QoS for different vehicular users in a FiWi assisted V2I network. According to [13], vehicular users generate different kinds of vehicular data traffic, namely advance driving, platooning, remote driving, and extended sensors. The vehicular data traffic is thus classified into four classes depending on its throughput, latency, and reliability requirements, also termed KPIs. The ONUs and RSUs are collocated and are collectively called ONU-RSUs. The received data at ONU is the same as that received at RSU. At ONU-RSUs the vehicular data traffic is assigned to the T-CONTs based on the priority of the vehicular data traffic. Thereafter, we propose a ML-based T-CONT priority assignment wavelength allocation algorithm that minimizes the number of wavelength switching instances in the PON. As the number of wavelength switching instances at ONU-RSU is minimized, the tuning latency at the ONU-RSU reduces, which minimizes the e2e latency of FiWi based V2I network. We compare the vehicular traffic prediction performance for various ML algorithms namely, linear regression, random forest, and CatBoost model. Thereafter, we utilized the predicted vehicular traffic from CatBoost model to allocate wavelength to the ONU-RSUs. Moreover, the performance of the proposed algorithm is compared with non-ML based approaches, namely random wavelength allocation and equal allocation algorithms.

6.3 System Description

The FiWi network consists of a TWDM-PON as the back-end network and IEEE 802.11p based V2I network as the front-end [54]. Our system model consists of an OLT located at the central office which communicates with ten ONUs placed along the highway through a 1:16 splitter. The ONUs are connected to the RSUs which in turn communicate with the end users that are vehicles. The passive splitter centralizes the communication between

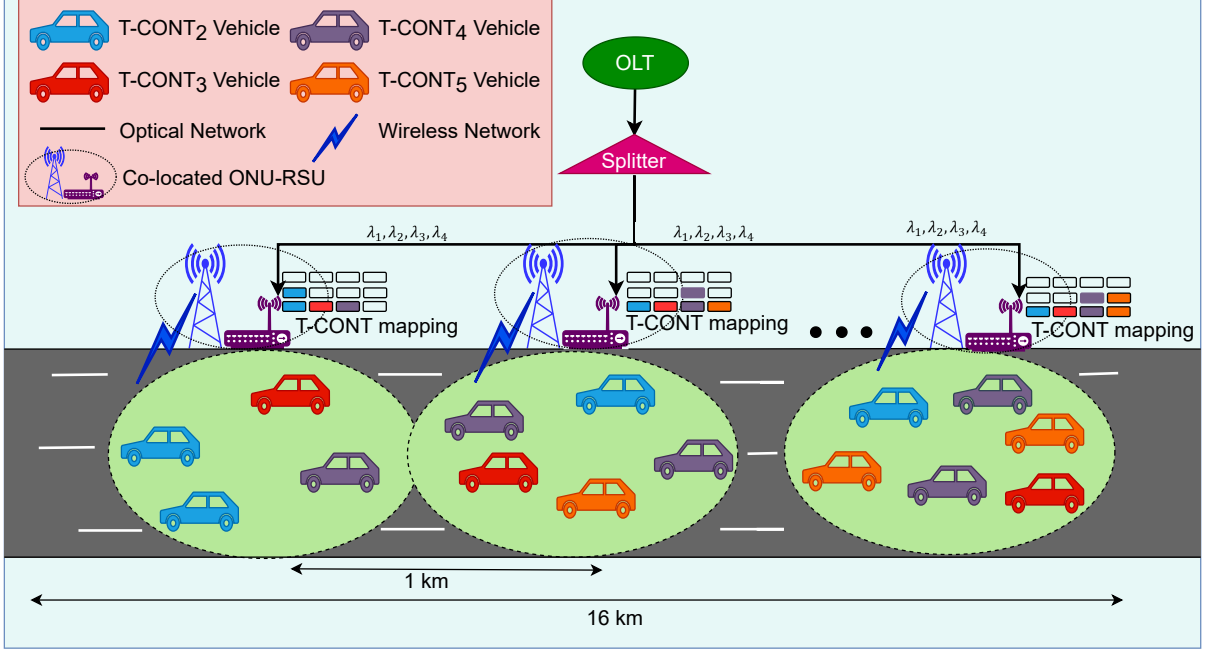


Figure 6.1: FiWi based V2I network

OLT and various users. Wavelength allocation is facilitated at the OLT based on the load served by each ONU which is the aggregate throughput of vehicles handled by them. The hourly traffic volume considered the interstate (IS)-94 highway between Minneapolis and Saint Paul and is taken from [129].

6.4 FiWi Enhanced Vehicular Communication

In this section the system model for the considered FiWi based V2I network is presented. In addition, a detailed classification for vehicular traffic is also presented in this section.

6.4.1 FiWi Based Vehicle-to-Infrastructure Network

As shown in Fig. 6.1, we consider a FiWi network consisting of a NG-PON2 as the backhaul and IEEE 802.11p based V2I network as the fronthaul. In this work, we consider vehicular networks as the vehicular network has critical safety and security requirements; thus, ensuring that the quality of services is met for vehicular traffic is a critical challenge

for the network. The OLT of NG-PON2 is located at the central office. The ONUs are connected to the OLT via a passive power splitter. All spectral components are available at each ONU, where the wavelength is selected. Moreover, each ONU is capable of handling adding/dropping of wavelengths and there are three configurations for the demultiplexer selection node— (a) demux using wavelength selective switches (WSS), (b) fixed arrayed-waveguide grating (AWG) and fiber cross-connect, and (c) power splitter with coherent receiver or tunable filter. The ONUs are collocated with RSUs and are collectively called ONU-RSUs. As ONU and RSU are collocated, the amount of vehicular data traffic received at the RSU is directly sent to the ONU [53]. There are T-CONTs available at the ONU that allocate the different network services to the vehicular data traffic based on the priority of the network traffic.

Among the five T-CONTs at the ONU, T-CONT₁ has the highest priority and is generally reserved for background traffic. Similarly, T-CONT₅ has the least priority and is assigned the data traffic with low priority. The T-CONT mapping is shown in Fig. 6.1 for T-CONT₂, T-CONT₃, T-CONT₄, and T-CONT₅ that shows the type of traffic load at each ONU-RSU. The T-CONT mapping at the ONU-RSU suggests the amount of high-priority vehicular data traffic available at the ONU-RSU. In this work, the priority of the data traffic is decided on the basis of latency, throughput, and reliability of the data traffic. In line with prior works, the ONU-RSUs are assumed to be collocated with the RSUs. The RSUs serve the vehicles through a wireless medium, and each vehicle can generate four classes of traffic that are assigned to the T-CONTs based on their priority. The vehicular traffic classification and assignment of traffic to different T-CONTs is defined in detail in later sections.

6.4.2 Vehicular Data Traffic Use Cases

In this subsection, we discuss the classification of vehicular data traffic and its use cases:

6.4.2.1 Vehicle Platooning

Vehicle platooning minimizes the distance between the vehicles and is used to accelerate a group of vehicles together. It includes the following use cases [12], [13]:

- Cooperative driving: It includes the exchange of platooning information among multiple vehicles. The e2e latency requirement of these services is in the range of 10-25 msec and the throughput required is in the range of 50-65 Mbps. These services require reliability of 90-99% and have minimum communication range of 80-350 m.
- Reporting: These services include the reporting information exchange between vehicles and RSUs. The e2e latency requirement for these services is 500 msec.
- Information sharing: The information exchange between vehicles and RSUs require an e2e latency of 20 msec, the throughput required is 50 Mbps and minimum communication range required is 180-350 m.

6.4.2.2 Advanced driving

The services for automated driving include collision avoidance, automated driving, and trajectory alignment. The KPIs for the use cases are defined below [13]:

- Cooperative collision avoidance: These services include collision avoidance information exchange among V2X users. The maximum tolerable e2e latency for these services is 10 msec, with a maximum throughput of 10 Mbps. These services require a high reliability of 99.99%.
- Automated driving (among vehicles): It requires information sharing among the vehicles. The maximum tolerable e2e latency for these services is 100 msec, with a maximum throughput of 53 Mbps. These services require a minimum communication range of 360-700 m.

- Automated driving (between vehicles and RSUs): These services require information transmission between vehicles and RSUs. The minimum requirement for e2e latency, throughput, and communication range is 100 msec, 50 Mbps, and 360-700 m, respectively.
- Emergency trajectory alignment: It includes trajectory alignment among the vehicles. The minimum e2e latency for such services is 3 msec. These services require a high reliability of 99.99%. The minimum communication range and throughput requirement for these applications is 500 m and 30 Mbps, respectively.
- Intersection safety information: These include the safety information among RSU and vehicles regarding intersections. The downlink and uplink throughput required for these services are 50 and 25 Mbps, respectively.
- Cooperative lane change: These include the transmission among vehicles to improve safety and change lanes effectively. These services require e2e latency in the range of 10-25 msec and reliability of 90-99%.
- Video sharing: These include video sharing between a vehicle and a V2X application server. These services require an uplink throughput of 10 Mbps.

6.4.2.3 Extended Sensors

In order to ensure the enhanced perception of the vehicular environment beyond what their own sensors can detect and get a holistic view of the on-road vehicular traffic, these data services include the exchange of data from the local sensors or live video data among the vehicles. Some of the use cases for extended sensors are as follows [12], [13]:

- Sensor information: These include sharing of sensor information among the vehicles. The range of e2e latency requirement for such services is 3-100 msec, reliability in the range of 95-99.99%, the minimum communication range for these applications is 50-1000 m, and the range of throughput requirement is 20-1000 Mbps.

- Video sharing: To ensure a holistic view of the road, these include live video sharing among vehicles. The range for e2e latency requirement for these services is 10-50 msec, throughput requirement is in the range of 10-700 Mbps, the range of reliability requirement is 90-99% and minimum communication range required is 100-400 m.

6.4.2.4 Remote Driving

These include information exchange between vehicle and vehicle-to-everything (V2X) application server for remotely operating the vehicle. The downlink throughput required for these services is 25 Mbps and uplink throughput requirement is 1 Mbps with maximum e2e latency of 5 msec and high reliability of 99.99% [13].

According to T-CONT to which these traffics are assigned, a priority is assigned to these traffic in order to provide relevant services to the end users. The assignment of traffic to different T-CONTs is defined in detail in Section 2.3.

6.4.3 T-CONT Assignment for V2X Traffic

In general, the traffic is assigned to the T-CONTs based on the desired service requirements of the users. For instance, in the prior works, the T-CONTs are assigned to different kinds of network traffic, namely voice, video, best-effort, and background traffic, based on their desired latency requirement. The background traffic has the highest priority; therefore, it was assigned T-CONT₁ of the ONU. The latency for voice traffic is the lowest and, therefore, is assigned T-CONT₂. This was followed by video and best-effort traffic, which were assigned T-CONT₃ and T-CONT₄, respectively. Similarly, in this work, we have assigned four classes of vehicular traffic depending on their KPI requirements. Thus, a class of traffic with high throughput, high reliability, and low latency requirement is prioritized more than the other classes. Remote driving has the maximum reliability requirement of 99.99%, while the other types of vehicular data traffic have lower reliability requirements. Thus, extended sensors are given the highest priority and assigned to T-CONT₂.

Table 6.1: KPIs for V2X use cases [13]

Use Case	latency (msec)	Reliability (%)	Throughput (Mbps)	T-CONT Assigned
Extended Sensors	3-100	90-99.99	10-1000	3
Advance driving	3-100	90-99.99	10-50	4
Remote driving	5	99.99	25	2
Platooning	10-500	90-99.99	50-65	5

Extended Sensors and advanced driving have a minimum latency requirement of 3 msec; however, the throughput requirement for extended sensors is higher and therefore, is given the second highest priority. Further, the minimum latency requirement for platooning is higher than the other vehicular data traffic and thus, is given the lowest priority and assigned to T-CONT₅. The detailed traffic assignment to different T-CONTs is given in Table 6.1.

6.5 ML-Based Vehicular Traffic Prediction

In this section, we discuss the on-road vehicular traffic predictions and the framework of various methods used for on-road vehicular traffic predictions.

Machine learning has emerged as a powerful tool for intelligent vehicular networks. Specifically, machine learning is employed in various scenarios to predict road traffic density and ensure a safe and reliable vehicular network. It can be easily inferred that accurate prediction of on-road traffic volume can aid the RSU to perform traffic mobility estimation by building the statistical traffic model and then improving QoS for vehicular users. In this work, we aim to predict the on-road vehicular traffic to generalize the information accurately given the complexity introduced by year-long changing traffic patterns and altered social, temporal, and weather conditions. This will help the vehicular network provide the resources effectively depending on the traffic volume on the road.

Recently, there has been an ongoing interest in the prediction of vehicular arrival rate using machine learning. For instance, [130] and [131] utilized artificial neural network (ANN) and LSTM model to achieve improved latency of the network. [130] proposed an efficient routing scheme to reduce the latency of the vehicular network while [131] utilized arrival rate prediction to improve the transmission latency of the vehicular network.

This work utilizes machine learning-based on-road traffic prediction for day-ahead traffic predictions. The on-road vehicular traffic prediction quantifies the number of vehicles connected to the RSUs at each hour. The envisioned machine learning scheme would be operated on the centralized server, wherein the data collection at RSUs is utilized for wavelength assignment at the ONUs. The collection of sensory data at the ONU-RSUs is very popular among researchers. The growth of sensor network has enabled vehicles are able to gather information about driver's environment, like speed, temperature, moisture, and road conditions, etc. Generally, the RSUs initiate the probing process and select the on-road vehicles as probes to collect traffic and environment information. A detailed explanation of RSU probing is given in [132]. Further, the authors in [133] discussed the switching of vehicular communication networks from cellular to RSU whenever there is an opportunity for a vehicle to offload vehicular data. This helps in improving the QoS of vehicular network by smartly ranking the RSUs in the network based on the collection of data at the RSUs. This is due to the fact that once the number of vehicles on the road is estimated, the vehicles are distributed on the road using poisson distribution. The vehicles generate four kinds of traffic as discussed in Section 6.4.2. The amount of traffic generated by each vehicle is proportional to the percentage of average throughput of each kind of vehicular data traffic. The percentage of vehicles generating T-CONT₃ is the highest followed by T-CONT₄, T-CONT₅, and T-CONT₂. The prediction of the number of vehicles on the road would quantify the number of vehicles connected to each RSUs using a known distribution.

Once the number of vehicles connected to each RSU is obtained, the amount and type

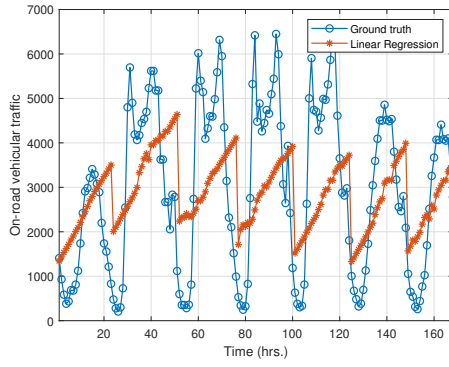
of daily vehicular data traffic available at each ONU-RSU can be obtained as the type of traffic at each ONU-RSU will follow the throughput of each vehicular traffic type. This will lead to selecting the heavily loaded ONU-RSUs in the FiWi-assisted V2I network, which can further be utilized to allocate the wavelength to ONU-RSUs based on the priority of vehicular data traffic.

The hourly data of on-road vehicular traffic was taken from [129]. The dataset presents an on-road vehicular traffic volume for the IS-94 highway between Minneapolis and Saint Paul. The dataset analyses hourly traffic volume on the road from 2012 to 2018. The given data set consists of the following features: time, date, year, day, holiday, and climatic conditions such as snow, rain, clouds, temperature, and traffic volume. This feature set transformation and expansion was done by adding the day of the week and weather description as categorical variables. In Fig. 6.2 the hourly profile of the number of vehicles connected to ONU-RSU is shown for January 1-7, 2018.

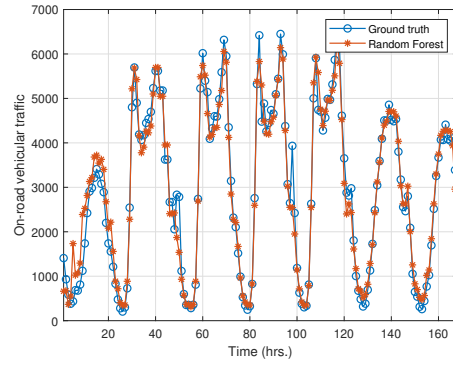
6.5.1 Training And Testing of Data Set

It was observed from the dataset that the traffic conditions have dynamic temporal dependency as the year progress. Consequently, according to the chronological years, we split the data set into training and testing subsets. The training data set contains data from 2012-2017, while the testing data consists of data for 2018. Thus, the data set consists of 2192 training samples and 365 testing samples. We used three models to test the prediction accuracy: Linear regression model, the Random forest model, and CatBoost model. The following metrics were used for comparison:

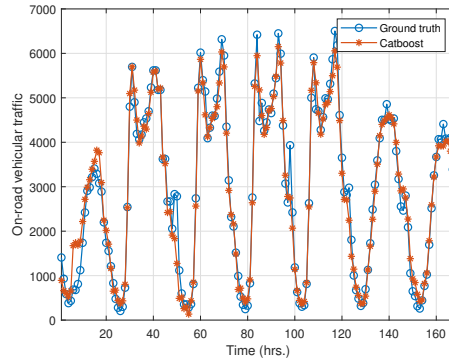
1. Root mean square error (RMSE)
2. R^2 score



(a) Linear Regressor Model



(b) Random Forest Regression



(c) CatBoost Model

Figure 6.2: Prediction accuracy for (a) Linear Regressor Model, (b) Random Forest Regression, and (c) CatBoost Model for January 1 to January 7, 2018.

Table 6.2: Prediction accuracy for different methods

Model	R^2 score	RMSE
Linear Regression	0.157	1811.48
Random Forest	0.945	459.04
CatBoost	0.952	429.26

6.5.2 Linear Regression Model

We chose the linear regression model as the baseline model to on-road vehicular traffic prediction. Fig. 6.2(a) shows the performance of the linear regression model for January 1 to January 7, 2018. It can be seen that linear regression does not perform well with the given data set. It is because the data set has time-series tendencies and violates the assumptions of a linear regression model. Thus, inaccuracies are expected. Further, the RMSE and R^2 score for the linear regression model is 1811.48 and 0.157, respectively as observed from Table 6.2.

6.5.3 Random Forest Model

The random forest model is an ensemble model that fits several classifying decision trees on various subsets of the input data set and feature set. To control the over-fitting and improve the prediction accuracy, the random forest model utilizes averaging over multiple decision trees. It has a non-linear nature that gives it an advantage over other linear algorithms. Further, a random forest regression model has advantages such as robustness against outliers, aberrant data, and skewed distributions. The performance of the random forest regressor model is shown in Fig. 6.2(b). The random forest regressor is chosen for on-road vehicular data prediction because of its non-parametric nature. We utilized a random forest regressor consisting of 200 estimators for prediction. It can be observed from Table 6.2 that random forest model performance is significantly improved from our baseline with an RMSE score of 459.04 and R^2 score of 0.945.

6.5.4 CatBoost Model

From the results, it is observed that the random forest regressor model performs well for the considered data set. However, the data set considers some categorical features in the feature set. Thus, numerical encoding can improve the efficiency of prediction. In random forest model, we utilize a mapping of categorical variables and numbers, resulting in the performance as noted in Fig. 6.2(b). Thus, a potential bias was observed from an implicit ordinality that was introduced as a result of the mapping in the random forest model. Thus, we utilized the CatBoost model which uses an ensemble method that natively allows training on categorical and numeric variables. From Fig. 6.2(c), it can be observed that the CatBoost model performs better than the linear regressor and random forest model. The R^2 score and RMSE score using CatBoost model are 0.952 and 428.26, respectively as show in Table 6.2. With the given size of the data set, the learning computation time is comparable across the multiple models tested. However, the CatBoost model provides an added advantage of being highly scalable as it is optimized for high-speed learning [134].

Thus, it can be inferred that methods such as linear regression are simple in nature and have low computational complexity compared to ensemble learning methods because they train only one learner. However, the ensemble learning methods have multiple learners and give better performance. Further, CatBoost model utilizes native optimization and offers the best performance in terms of accuracy. Thus, in this work, we utilized Catboost model to predict on-road vehicular traffic. The vehicles are then distributed among the ONU-RSU using poisson distribution. This distribution of vehicles leads us to compute the number of vehicles connected to an ONU-RSU. Thereafter, the vehicular traffic distribution at the ONU-RSU is calculated as the number of vehicles generating the particular type of vehicular traffic is proportional to the throughput of the vehicular traffic. To maintain the KPIs for different categories of vehicular data traffic, it is essential to minimize the end-to-end latency of the network. As wavelength allocation is one of the critical

parameters in TWDM-PON, thus, the wavelength must be assigned to the ONU-RSUs such that the end-to-end latency of the network is minimized. This is done by minimizing the tuning latency of the network, i.e., by minimizing the number of wavelength switching instances at the ONU-RSU. Each wavelength switching instance incurs some latency, and frequent switches in wavelength affect the e2e latency of the V2I network. Thus, in this work, we assign the wavelength to the ONU-RSUs according to the priority of data traffic generated by the vehicles connected to it. Hence, if we are able to quantify the amount and the type of traffic at each ONU-RSU for a $T_H = 24$ hour duration, we can assign the wavelength to the ONU-RSUs based on the quantity of high-priority traffic on these ONU-RSUs and minimize the number of wavelength-switching instances at the ONU-RSU with high priority data traffic. This can be done by utilizing ML prediction for T_H hour vehicular traffic profiles. In this work, we utilize CatBoost model to predict the on-road vehicular traffic, which quantifies the load at each collocated ONU-RSU and RSU unit. Thereafter, we utilize ML-based T-CONT priority assignment wavelength allocation algorithm to allocate the wavelength to the ONU-RSUs based on the priority of vehicular data traffic and minimize the number of wavelength switching instances at the ONU-RSU. The proposed ML-based approach is compared with the other non-ML based approaches, namely random wavelength allocation and equal T-CONT based allocation algorithm in terms of throughput, latency, and reliability of the V2I network. The proposed algorithm requires a centralized server that processes the information of the overall network and assigns the wavelength to the ONUs. Although the proposed algorithm improves the QoS for vehicular users, some of the inherent challenges to the practical application of the proposed ML-based T-CONT algorithm in real scenarios include large computation resources required at the centralized server to process the information for the vehicular traffic. The proposed algorithm would require higher complexity as an ML model has to be implemented to allocate the proposed ML-based T-CONT prioritization-based wavelength allocation algorithm. In addition to the computation resources, the

implementation of the machine learning model and processing of data will require more energy compared to non-ML based models.

6.6 Problem Formulation

The fundamental problem under consideration is then cast as an optical latency minimization problem, which is dependent on the minimization of the number of wavelength switching instances at the ONU-RSU and is subject to the following set of constraints:

$$(P1) \min_{N_{WS}} \sum_{t=0}^{T_H-1} \sum_{k=2}^5 D_k^O(t), \quad (6.1a)$$

$$s.t. \quad \sum_{i=1}^{N_{ONU-RSU}} U_{v,i} \leq 1, \quad (6.1b)$$

$$D_k^{T-CONT}(t) \leq D_k^{th}, \quad \forall t \in [0, T_H - 1], \quad k \in [2, 5], \quad (6.1c)$$

$$\sum_{t=0}^{T_H-1} \sum_{k=2}^5 D_k^{T-CONT}(t) = \sum_{t=0}^{T_H-1} \sum_{k=2}^5 D_k^O(t) + D_k^W(t), \quad (6.1d)$$

$$D_2^{T-CONT}(t) < D_3^{T-CONT}(t) < D_4^{T-CONT}(t) < D_5^{T-CONT}(t), \quad \forall t \in [0, T_H - 1], \quad (6.1e)$$

where $D_k^O(t)$ is the optical latency of k^{th} T-CONT traffic at time t , N_{WS} is the number of wavelength switching instances at the ONU-RSU, T_H is the number of time slots, $N_{ONU-RSU}$ is the number of RSUs in the network, $U_{v,i}$ denotes the association of vehicle v with the i^{th} RSU, $D_k^{T-CONT}(t)$ is the latency of the k^{th} T-CONT at time t , where $k \in [2, 5]$, D_k^{th} is the latency threshold of k^{th} T-CONT, $D_k^O(t)$ and $D_k^W(t)$ is the optical and wireless latency of k^{th} T-CONT traffic at time t , respectively. In problem (P1), the first constraint (6.1b) assures the association of the vehicle with the RSU such that each vehicle is connected with only one RSU. Constraint (6.1c) ensures that the end-to-end latency requirement of each T-CONT is maintained within the ITS standard. In constraint (6.1d) the e2e latency of FiWi based V2I network is presented. This e2e latency

is a combination of optical link latency and wireless link latency. Further, constraint (6.1e) ensures that the priority of the T-CONTs is maintained. We consider $T_H = 24$ hour to minimize the number of hourly wavelength switching instances during an entire day. The overhead latency is taken as $16 \mu\text{s}$ [135]. The latency thresholds for different T-CONTs are considered as: $D_2^{\text{th}} = 50 \text{ msec}$, $D_3^{\text{th}} = 10 \text{ msec}$, $D_4^{\text{th}} = 10 \text{ msec}$, and $D_5^{\text{th}} = 25 \text{ msec}$ [13].

The above problem is solved using the following wavelength allocation algorithms: 1) Equal T-CONT based wavelength allocation algorithm, 2) Random wavelength allocation algorithm, and 3) Proposed ML-based T-CONT priority assignment wavelength allocation algorithm. The ML-based T-CONT priority assignment wavelength allocation algorithm utilizes the prediction of the number of vehicles on the road. The distribution of the traffic to the RSUs and type of traffic generated by the vehicles are of known distribution. Thus, the prediction of the number of vehicles on the road would quantify the amount and type of hourly vehicular data traffic available at each ONU-RSU. It has been shown later that the proposed ML-based T-CONT priority assignment algorithm achieves a good compromise between latency minimization, throughput maximization, and reliability enhancement.

6.6.1 Proposed ML-Based T-CONT Priority Assignment Wavelength Allocation Algorithm

This subsection presents ML-based T-CONT priority assignment wavelength allocation algorithm. The proposed algorithm minimizes the latency of the optical network by minimizing the number of wavelength switching instances at the ONU-RSU for a given initial information about the amount of traffic generated by the vehicular network, the number of wavelengths available to the ONU-RSUs, and the capacity of each wavelength in the network. The proposed wavelength allocation algorithm is summarized in Algorithm 5.

To allocate a wavelength to each ONU-RSU, we initially compute the load at each ONU-RSU. In order to do so, we consider a distance based association between RSUs and vehicles. Consequently, a vehicle is associated with the nearest RSU. Depending on

the number of vehicles, the traffic generated by each vehicle connected to the RSU is obtained. The type of traffic generated by each vehicle is dependent on the proportion of each T-CONT traffic¹ as shown in Table 6.1. Thereafter, the load at each ONU-RSU is calculated using the predicted on-road vehicular traffic and the type of traffic generated by each vehicle. We assume that as the ONU-RSUs are collocated with the RSUs, the traffic at the ONU-RSU is the same as that received by the RSUs. Utilizing the T_H hour load profile that is predicted using ML and the type of vehicular traffic, the sorting of ONU-RSUs is done based on the priority of traffic as follows and assigned to $\mathcal{N}_{\text{sort}}$:

$$\sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_2^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_3^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_4^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_5^{\text{T-CONT}}}, \quad (6.2)$$

where $\mathcal{N}_{\text{ONU-RSU}_k^{\text{T-CONT}}}$ denotes the set of ONU-RSUs with T-CONT k traffic, where $k \in [2, 5]$. It implies that the ONU-RSUs with highest amount of T-CONT₂ traffic is given more priority, followed by ONU-RSUs with the highest amount of T-CONT₃, T-CONT₄, and T-CONT₅ traffic. The data traffic for the N_w ONU-RSUs with the highest priority data traffic is assigned to the fixed wavelength bins B_1 , B_2 , B_3 , and B_4 , respectively.

Afterward, for the rest of the ONU-RSUs in $\mathcal{N}_{\text{sort}}$, a cut-off for the total number of T-CONTs of type ' k ' that can be accommodated in a wavelength bin is calculated for rest of the ONU-RSUs as follows:

$$CB_{i,k} = \left\lceil \frac{\text{Total number of T-CONTs of type } k}{\text{Total number of wavelength bins}} \right\rceil, \quad (6.3)$$

$$CB_{i,k} = \left\lceil \frac{\sum_{n=1}^{N_{\text{ONU-RSU}}} \text{T-CONT}_k^n}{N_w} \right\rceil, \quad (6.4)$$

where cut-off is denoted by $CB_{i,k}$, where ' i ' represents the i^{th} wavelength bin, B_i and ' k '

¹These proportion T-CONT traffic is based on the data rate of each T-CONT traffic, i.e., the more the data rate of the traffic, the higher will be the proportion of the traffic.

represents the type of traffic in the T-CONT, $T\text{-CONT}_k^n$ denotes the number of T-CONTs of type k at n^{th} ONU, $N_{\text{ONU-RSU}}$ is the number of ONU-RSUs in the network, N_w is the number of wavelengths, and $\lceil \cdot \rceil$ denotes the ceiling function. Thereafter, depending on the priority of the traffic and cut-off, the wavelength is allocated to the ONU-RSU.

An example of the proposed ML-based T-CONT prioritization based wavelength allocation algorithm is shown in Fig. 6.3. We consider a scenario with two wavelengths and 5 ONU-RSUs. It can be seen that first, the ONU-RSUs are sorted according to the priority of data traffic in T_H hours. ONU-RSU₁ has the highest higher priority data traffic, and T-CONT₅ has the lowest priority data traffic. As $N_w = 2$, thus, the wavelength for ONU-RSU₁ and ONU-RSU₂ are fixed to λ_1 and λ_2 , respectively. For the rest of the three ONU-RSUs, the wavelength is assigned at each hour according to the type of data traffic. This is in line with [136] that utilized hourly traffic variation to design a protection path for hourly bandwidth requirement. It can be seen that the wavelength for ONU-RSU₁ and ONU-RSU₂ are fixed at each hour, and there are no wavelength switching instances for these ONU-RSUs. However, for ONU-RSU₃, there is a wavelength switching at $(t + 2)^{th}$ and $(t + 3)^{th}$ hours. Hence, there are 2 wavelength switching instances for ONU-RSU₃ in four hours. Similarly, for ONU-RSU₄ and ONU-RSU₅, there are 1 and 2 wavelength switching instances, respectively. These wavelength-switching instances incur a latency at the ONU-RSU and impact the end-to-end latency of the FiWi network. Hence, in the proposed algorithm, depending on the priority of data traffic at the ONU-RSU, the wavelength is assigned to the ONU-RSU to minimize the number of wavelength switching instances in the network and minimize the end-to-end latency of the FiWi network.

6.6.2 Equal T-CONT based wavelength allocation algorithm

Equal T-CONT based wavelength allocation algorithm allocates the wavelength to the ONU-RSUs such that there is an equal load on all the wavelengths. This is done so that no wavelength is under-utilized or over-utilized. In an equal T-CONT based wavelength

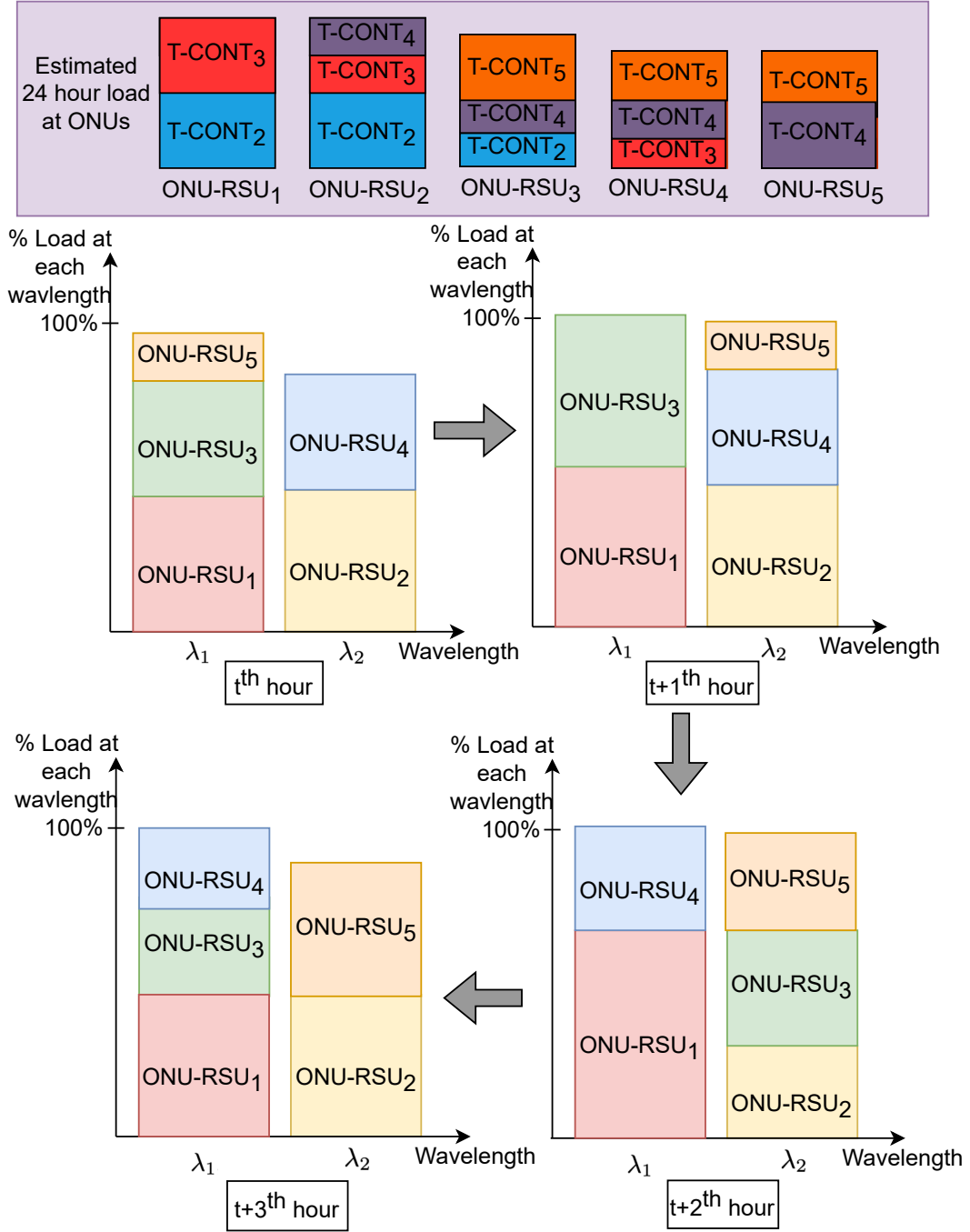


Figure 6.3: Example of proposed wavelength allocation algorithm

Algorithm 5 ML-based T-CONT prioritization based wavelength allocation algorithm

Input: The number of vehicles on the road, the type of traffic generated by each vehicle and the available set of bandwidths.

- 1: The vehicles are initially associated with the RSUs based on distance between RSUs and vehicle.
- 2: Calculate the load at each ONU-RSU based on the number of vehicles connected to each RSU and the type of traffic generated by each vehicle.
- 3: Based on the priority of vehicular traffic at each ONU-RSU, sort the ONU-RSUs as follows and assign it to $\mathcal{N}_{\text{sort}}$:

$$\sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_2^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_3^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_4^{\text{T-CONT}}} > \sum_{t=0}^{T_H-1} \mathcal{N}_{\text{ONU-RSU}_5^{\text{T-CONT}}}.$$

- 4: The data traffic for the N_w ONU-RSUs with the highest priority data traffic are assigned to the fixed wavelength bins B_1 , B_2 , B_3 , and B_4 , respectively.
- 5: Thereafter, for rest of the ONU-RSUs in $\mathcal{N}_{\text{sort}}$, a cut-off for the number of T-CONTs of type k (T-CONT $_k$) that can be accommodated in a wavelength bin, B_i is calculated as:

$$CB_{i,k} = \left\lceil \frac{\sum_{n=1}^{N_{\text{ONU-RSU}} - N_{N_w}} \text{T-CONT}_k^n}{N_w} \right\rceil.$$

- 6: **for** each ($N_{\text{ONU-RSU}} - N_{N_w}$) ONU-RSU **do**
 - 7: **if** the number of ONU-RSUs in B_1 is less $CB_{1,1}$ **then**
 - 8: Assign the wavelength bin B_1 .
 - 9: Update the number of T-CONTs at the ONU-RSU by decreasing the number of T-CONTs allocated to the ONU-RSU.
 - 10: **else**
 - 11: Repeat step (6) for wavelength bins B_2 , B_3 , or B_4 sequentially.
 - 12: **end if**
 - 13: **end for**
-

allocation algorithm, initially, the load at each ONU-RSU is calculated. The network load is then divided among the wavelengths such that each wavelength has an equal number of T-CONTs of each type. The cut-off for the number of T-CONTs of type k that can be accommodated in each wavelength is calculated depending on the total number of T-CONTs of each class and the total number of wavelengths available in the network. Based on this cut-off, the wavelength is allocated to each ONU-RSU. A similar approach is also presented in [62] where the authors designed a dynamic wavelength and bandwidth allocation algorithm for NG-PON2.

6.6.3 Random Wavelength Allocation Algorithm

In random wavelength allocation algorithm, initially, we calculate the load at each ONU-RSU. Depending on the load, the wavelength is assigned randomly to the ONU-RSU depending on the wavelength to which the ONU-RSU load fits. This is a random allocation strategy wherein according to the capacity of each wavelength bin, the wavelength is allocated.

6.6.4 Latency Analysis

This section presents the performance analysis for FiWi assisted V2I network. The e2e latency for the FiWi network is calculated by adding the latency for the optical and V2I network. The latency at the j^{th} ONU at t^{th} hour is calculated as [135]:

$$D_{ONU_j}(t) = (D_{oh} + D_{tuning}(t))/(1 - \Lambda_{ONU-RSU_j}(t)), \quad (6.5)$$

where D_{oh} is the latency due to overheads at the ONU-RSU, D_{tuning} is the tuning time from one wavelength to the next. According to ITU-T G.989.2, there are following three classes of wavelength tuning latency: a) slow (25 ms to 1 s), b) middle (10 microseconds (μs) to 25 ms), and c) fast ($< 10 \mu s$) [137]. Consequently, we have considered a middle tuning latency of $50 \mu s$ [137]–[139]. Thus, the wavelength tuning latency is considered as follows:

$$D_{tuning} = \begin{cases} 50 \mu sec, & \text{if wavelength switching} \\ 0 \mu sec, & \text{otherwise,} \end{cases} \quad (6.6)$$

i.e., $D_{tuning}(t) = 0$ if there is no switching of wavelength at the hour t , else $D_{tuning}(t) = 50 \mu s$ [135]. In this work, we consider an hourly wavelength switching design wherein the wavelength can be switched at each hour depending on the priority of traffic at the ONU-RSUs. $\Lambda_{ONU-RSU_j}(t)$ is the normalized load of ONU-RSU $_j$ on a wavelength at time t . The overhead latency is taken as $16 \mu s$ [135].

The latency for the optical link, i.e., between j^{th} ONU and OLT is a combination of latency at the ONU, propagation latency which is given by $D_{tr}(D_{o,s} + D_{s,ONU})$, queuing latency, and processing latency. Here, $D_{o,s}$ and $D_{s,ONU}$ are the OLT-splitter distance and splitter ONU distance, respectively [140].

$$D_{O_j} = D_{ONU_j} + D_{tr}(D_{o,s} + D_{s,ONU}) + D_Q + D_P. \quad (6.7)$$

where D_Q is the queuing latency and D_P is the processing latency. In this work, we have considered queuing latency, $D_Q = [0, 1000] \mu sec$ and processing latency $D_P = 200 \mu sec$ [140].

For wireless network, the latency at vehicle v for a pre-defined throughput $R_k(\Gamma_v, L_v, \epsilon)$ can be calculated as [141]:

$$D_w = \left[\frac{\sqrt{B}Q^{-1}(\epsilon) \log_2(e) \sqrt{1 - (1 + \Gamma_v)^{-2}}}{B \log_2(1 + \Gamma_v) - R_k(\Gamma_v, L_v, \epsilon)} \right]^2, \quad (6.8)$$

where B is the bandwidth at each ONU-RSU, ϵ is the reliability, $R_k(\Gamma_v, L_v, \epsilon)$ is the maximum achievable ergodic rate of the vehicle v given in [141], Γ_v is SINR at v^{th} vehicle given by $p_v \Psi_v$ for zero forcing receiver, Ψ_v is given $\frac{\chi_v \beta_v (M-K)}{P_B \beta_v (1-\chi_v) + M\sigma^2}$, M is the number of antennas at RSU, χ_v is the estimation accuracy, K is the number of vehicles to which RSU is connected [141]. The value for each parameter is mentioned in Table 6.3. Further, the e2e latency of V2I link is calculated by using the latency of optical and wireless link given in (6.5) and (6.8), respectively.

Similarly, for a given latency requirement, L_v , the achieved V2I throughput for URLLC system is given as [141]:

$$R_k(\Gamma_v, L_v, \epsilon) = B \log_2(1 + \Gamma_v) - \sqrt{\frac{B}{L_k}} \log_2(e) Q^{-1}(\epsilon) \sqrt{1 - (1 + \Gamma)^{-2}}. \quad (6.9)$$

It is assumed that the optical fiber cable has negligible packet loss [142]. Thus, the

Table 6.3: Parameters for simulation

Parameter	Definition	Value
$D_{o,s}$	OLT-splitter distance	2.2 km [140]
t_T	Transport latency/Propagation latency	5 μ s [140]
t_Q	Queuing latency	60 μ s [140]
t_P	Processing latency at OLT	200 μ s [140]
$N_{\text{ONU-RSU}}$	Number of ONU-RSUs	16 [53]

the throughput of the vehicular network is assumed to be bounded by the V2I network throughput.

6.6.5 Complexity Analysis

The proposed ML-based T-CONT prioritization-based wavelength allocation algorithm utilizes CatBoost model for predicting the on-road vehicular traffic. In addition to predicting the on-road traffic, the proposed algorithm also utilizes a sorting method to sort the ONUs based on the predicted vehicular traffic. Hence, the complexity of the proposed algorithm is given as $\mathcal{O}(N_{\text{ONU-RSU}} \log(N_{\text{ONU-RSU}}) + n|C|)$, where $\mathcal{O}$ is the big-O notation, $N_{\text{ONU-RSU}}$ is the number of ONU-RSUs in the network, n is the number of examples in CatBoost classifier, and C is the number of numerical features, each providing a number of split candidates [143]. Similarly, the complexity of random wavelength allocation is $\mathcal{O}(N_{\text{ONU-RSU}})$ as the wavelengths are assigned randomly at the ONU-RSUs. Moreover, equal T-CONT based wavelength allocation requires only the sorting of ONU-RSUs based on the vehicular data traffic. Thus, the complexity of equal T-CONT based wavelength allocation is $\mathcal{O}(N_{\text{ONU-RSU}} \log(N_{\text{ONU-RSU}}))$. The complexity of different wavelength allocation algorithms is compared in Table 6.4.

Table 6.4: Complexity analysis for wavelength allocation algorithms

Algorithm	Complexity
ML-based T-CONT prioritization-based wavelength allocation algorithm	$\mathcal{O}(N_{ONU-RSU} \log(N_{ONU-RSU}) + n C)$
Random wavelength allocation	$\mathcal{O}(N_{ONU-RSU})$
Equal T-CONT based wavelength allocation	$\mathcal{O}(N_{ONU-RSU} \log(N_{ONU-RSU}))$

6.7 Performance Evaluation

We considered a 16000 m $\times$ 200 m segment of IS-94 highway between Minneapolis and Saint Paul. The hourly on-road vehicular traffic data was taken from the Minnesota Department of Transportation (MnDOT) data set [129]. The hourly vehicular traffic is distributed to the ONU-RSUs using Poisson distribution. Each vehicle can generate four kinds of traffic as mentioned in Table 6.1. These vehicles are connected to the RSUs using wireless links. The ONUs are collocated with the RSUs and are collectively called ONU-RSUs. The considered ONUs are tunable ONUs, i.e., each ONU can be tuned to any of the available wavelengths. We consider that the number of wavelengths available to the ONUs is four. The distance between two RSU units is considered to be 1 km [144], [145]. The distance between OLT and splitter is considered to be 2.2 km [140]. The transportation, queuing, and processing latency of PON is considered to be 5 μ s, 60 μ s, and 200 μ s, respectively. For simulations, we have fixed the queuing latency to 60 μ s; however, the queuing latency is generally of the order of micro seconds [135], [140] and, therefore, would not significantly affect the e2e latency. The impact of queuing latency on the e2e latency is further explained later. Table 6.3 summarizes the parameters used for the simulation of FiWi assisted V2I network. For simulations, we have integrated Python based on-road traffic prediction with MATLAB.

The average number of wavelength switching instances for each T-CONT in $T_H = 24$ hours is shown in Fig. 6.4. It can be observed that for random and equal T-CONT

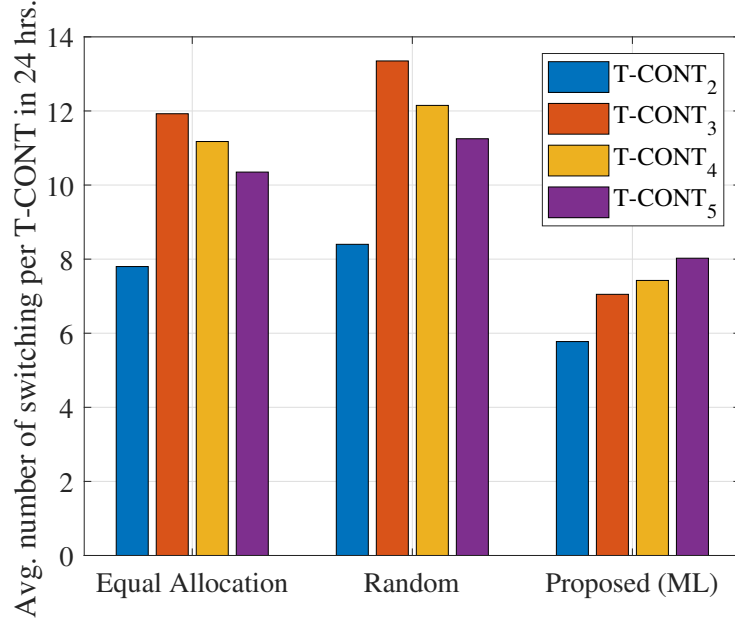


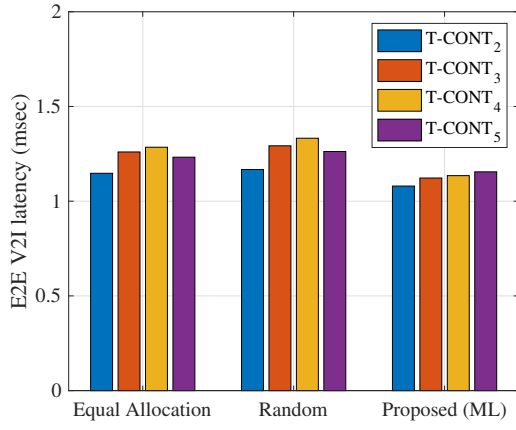
Figure 6.4: Average number of wavelength switching instances per T-CONT for each ONU-RSU in 24 hours.

based wavelength allocation algorithms, the number of wavelength switches of different T-CONTs is proportional to the traffic at each T-CONT. This implies that the T-CONT with a higher amount of data traffic will incur a higher number of wavelength switching instances and, therefore, will incur a higher amount of delay and vice versa. Further, it can also be observed that for equal T-CONT based wavelength allocation and random wavelength allocation the priority of the data traffic does not play a role. However, for the proposed ML-based T-CONT priority assignment algorithm, the number of wavelength switching is proportional to the priority of each T-CONT. Further, the number of wavelength switches is highest for the random wavelength allocation algorithm followed by an equal T-CONT based wavelength allocation algorithm and is the least for the proposed wavelength allocation algorithm. Specifically, the average number of wavelength switching instances per T-CONT reduces by 37.5% and 44.44% for T-CONT₃ for random and equal wavelength-based allocation algorithms, respectively, as compared to the proposed approach. This impacts the e2e latency of the network as shown in Fig. 6.6. In accordance to ITU-T, the following three classes as the wavelength tuning latency are considered: a)

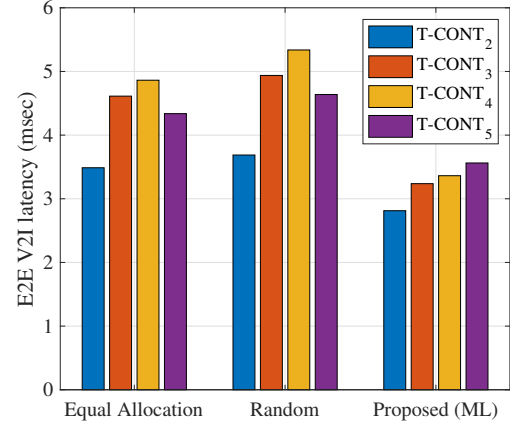
slow (25 ms to 1 s), b) middle (10 μ s to 25 ms), and c) fast ($< 10 \mu$ s) [137]. Thus, we have compared the performance of the different wavelength allocation schemes for different wavelength tuning latencies in Fig. 6.5. It can be observed that for slow wavelength switching, the QoS requirement of the users is not met for all the T-CONTs. This is because the wavelength tuning latency is very high, which increases the end-to-end latency of the vehicular network. However, for middle and fast wavelength tuning latencies, the QoS of the vehicular traffic is met.

The e2e latency for FiWi based V2I network has been depicted in Fig. 6.6. It can be observed that the latency for the proposed ML based wavelength allocation algorithm is the least followed by equal T-CONT allocation and random wavelength allocation algorithm. Further, it can be seen that for random and equal T-CONT-based wavelength allocation algorithms, the latency of the different T-CONTs is proportional to the traffic at each T-CONT. However, for the proposed T-CONT prioritization algorithm, the e2e latency follows the same trend as the priority of the T-CONTs, i.e., T-CONT₂ has the highest priority, i.e., least latency followed by T-CONT₃, T-CONT₄, and T-CONT₅. Specifically, the end-to-end V2I latency per T-CONT reduces by 32.98% and 39.81% for T-CONT₃ for random and equal wavelength-based allocation algorithms, respectively, as compared to the proposed approach. Similarly, for T-CONT₁, the end-to-end V2I latency per T-CONT reduces by 16.17% and 22.97% for random and equal wavelength-based allocation algorithm, respectively, as compared to the proposed approach

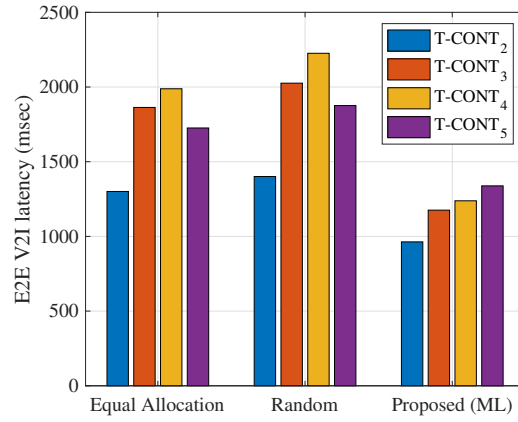
Fig. 6.7 shows the variation of e2e latency of the V2I network with respect to queuing latency for high priority T-CONT, i.e., T-CONT₂ and low priority T-CONT, i.e., T-CONT₄. It can be seen that the e2e latency performance is linearly varying with respect to queuing latency. It is interesting to note that the queuing latency is usually very low, i.e., of the order of microseconds due to which it does not affect the e2e performance of the V2I network. It can be seen that for random wavelength allocation, the e2e latency is the highest, followed by equal T-CONT based wavelength allocation followed by the



(a)



(b)



(c)

Figure 6.5: E2E latency for different wavelength tuning latency classes: a) Fast wavelength tuning (5μ s), b) Middle wavelength tuning (50μ s), and c) Slow wavelength tuning (25 ms).

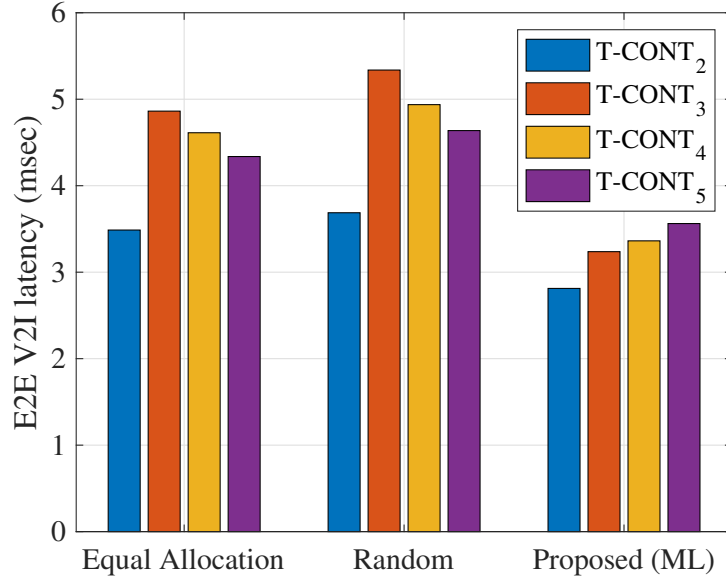


Figure 6.6: E2E latency for V2I network.

proposed wavelength allocation algorithm. Further, it is interesting to note from Fig. 6.7 that even for the worst case queuing latency of 1 msec, the performance for the FiWi network is within the latency requirement of 5 msec for T-CONT₂ using the proposed wavelength allocation algorithm.

Fig. 6.8 shows the variation of achievable throughput with respect to the reliability of the V2I link. It is well known that as the reliability of the network increases, the packets can reach the destination more reliably, and the overall throughput of the V2I network increases. This can be observed from Fig. 6.8, specifically, for stringent latency requirement of the V2I link, i.e., for $D_{V2I} = 0.01$ msec, there is an increase in throughput from 38 Mbps to 44 Mbps as reliability increases from 10^{-6} to 10^{-1} . Further, as the e2e latency requirement of the user increases, the vehicle can accommodate more traffic within the same e2e latency requirement. This variation in throughput decreases as the latency requirement of the network is relaxed from $D_{V2I} = 0.01$ msec to $D = 10$ msec. Furthermore, with the increase in latency requirement, the achieved throughput is close to the ergodic rate. In addition, it is interesting to note that there is only a slight increase

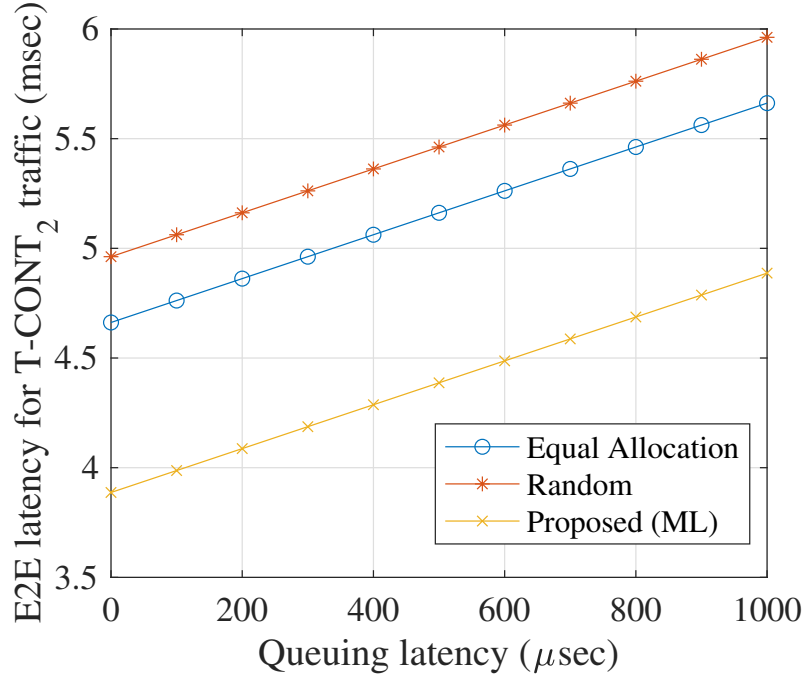


Figure 6.7: E2E latency for T-CONT₂ with respect to queuing latency.

in achievable network throughput with the change in latency from 1 msec to 10 msec, i.e., the latency requirement of T-CONTs in the V2I network, thus, the achievable throughput of the T-CONTs is not much affected much with the change in network load as can be observed from Fig. 6.9.

Fig. 6.9 presents the achievable throughput per vehicle for each T-CONT. The throughput of each T-CONT depends on the amount of bandwidth allocated to each T-CONT. It is worthwhile to note that the bandwidth allocated to each T-CONT is assigned in proportion to the network load. That signifies that T-CONT with a higher load will be allocated higher bandwidth and vice versa. This results in equal allocation of bandwidth per load in the network. Since, the bandwidth per load is similar for each T-CONT, thus, the throughput per user for each T-CONT is similar. Further, it can be observed that using the proposed algorithm, the required performance can be met for up to 100% loaded network for T-CONT₂, T-CONT₃, and T-CONT₄. However, the throughput requirement of T-CONT₅ is met only for 65% of the network load. This is because T-CONT₅ has

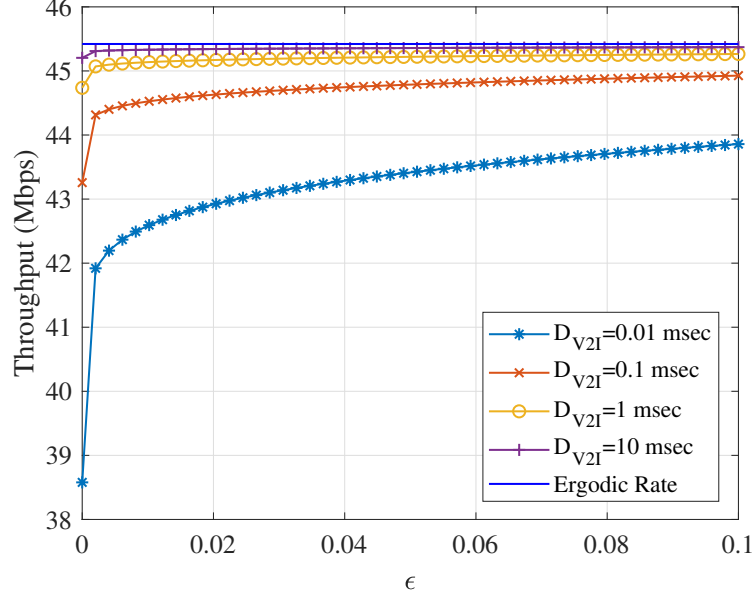


Figure 6.8: Throughput with respect to latency and reliability for V2I link for 70% network load.

the least priority and, therefore, is not able to meet the throughput requirement for high network load. Further, it is interesting to note that delay requirements of the different T-CONTs have no impact on the throughput of the V2I network. It is due to the fact that the e2e delay requirement for the different T-CONTs of the V2I network has a very slight impact on the throughput achieved by the V2I network as can be seen from Fig. 6.8.

The e2e link reliability for all the T-CONTs of the FiWi-based V2I network is calculated as follows:

$$P_T^S = P_{V2I}^S \cdot P_V^S \cdot P_{RSU}^S \cdot P_{ONU-OLT}^S, \quad (6.10)$$

where P_{V2I}^S , P_V^S , P_{RSU}^S is the V2I link reliability, vehicle equipment reliability, and the reliability of RSU, respectively. $P_{ONU-OLT}^S$ is the probability of successful transmission from ONU-RSU to OLT. The failure of V2I transmission can be denoted as:

$$P_T^F = 1 - P_T^S = 1 - (1 - P_{V2I}^F)(1 - P_V^F)(1 - P_{RSU}^F)(1 - P_{ONU-OLT}^F), \quad (6.11)$$

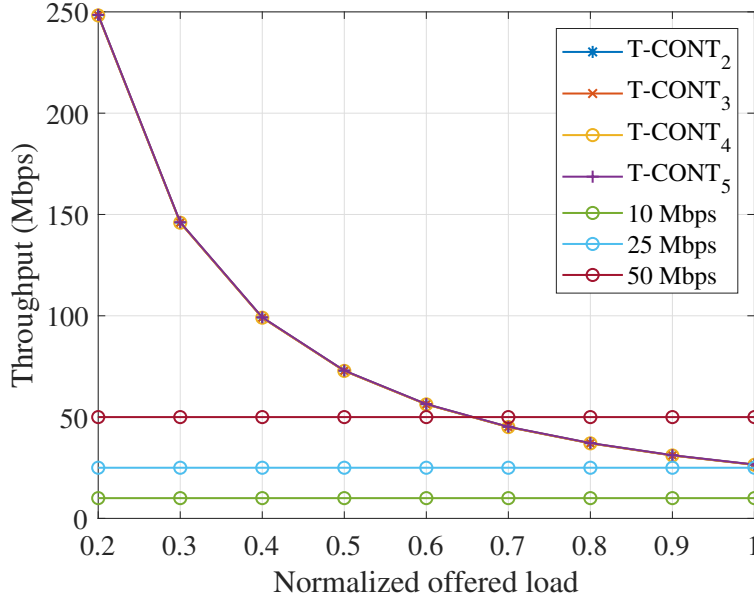


Figure 6.9: Throughput at each vehicle for the proposed ML-based T-CONT priority assignment algorithm.

where P_{V2I}^F , P_V^F , and P_{RSU}^F are the probability of failure of V2I link, vehicle equipment, and RSU, respectively. $P_{ONU-OLT}^F$ is the probability of failure of transmission from ONU to OLT, which is given by:

$$P_{ONU-OLT}^F = 1 - (1 - P_{ONU}^F)(1 - P_C^F)(1 - P_{cong}^F), \quad (6.12)$$

where P_{ONU}^F denotes the probability of failure of ONU, P_{cong}^F is the probability of failure of transmission due to optical network congestion, and P_C^F is the probability of fiber cut. Thus, reliability for V2I transmission is given as:

$$P_T^S = 1 - P_T^F = (1 - P_{V2I}^F)(1 - P_V^F)(1 - P_{RSU}^F)(1 - P_{ONU}^F)(1 - P_C^F)(1 - P_{cong}^F). \quad (6.13)$$

It can be observed from Fig. 6.10 that with the increase in wireless link failure, the reliability of the network decreases. Further, it can also be seen that as the probability of fiber cut (P_f) increases, the reliability of the network decreases. Moreover, for a high

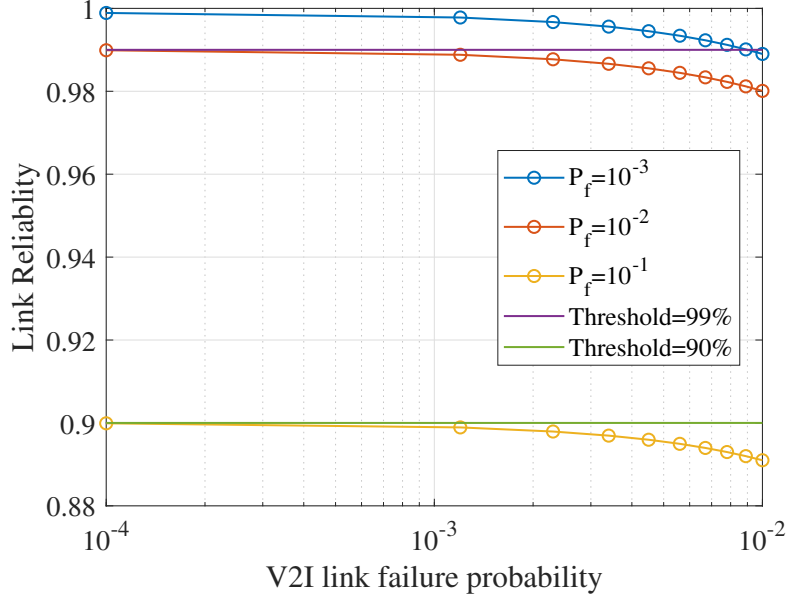


Figure 6.10: Link Reliability for V2I link for $P_V^F = P_{RSU}^F = P_{ONU}^F = P_{cong}^F = 10^{-6}$.

probability of fiber cut failure, i.e., $P_f = 10^{-1}$, the network is not able to meet the reliability threshold of 99%, i.e., it is not suitable for high priority T-CONT₂ traffic, however, for other T-CONTs, the reliability requirement of the network is met for V2I link failure probability of 10^{-3} . However, as the fiber cut failure decreases to 10^{-2} , the network is able to meet the reliability requirement of T-CONT₂ only for wireless failure probability of less than 10^{-3} . Similarly, if the probability of fiber cut decreases to 10^{-3} , the network is able to meet the reliability requirements of T-CONT₂ for wireless failure probability less than 10^{-2} . For the other T-CONTs, the reliability requirement is met for higher V2I link failure probabilities as well. Thus, if fiber cut probability is high, then the network may not be able to meet the reliability requirement of T-CONT₂ for high V2I link failure probability. While for the other T-CONTs, the reliability requirement of the network could be met even for high fiber cut probability.

Fig. 6.11 compares the link reliability for V2I link for $P_{cong}^F = 10^{-3}$ and $P_{cong}^F = 10^{-2}$. It can be observed that as the network congestion increases, the link reliability of the V2I link decreases. Specifically, the link reliability decreases by 1% for a probability of fiber

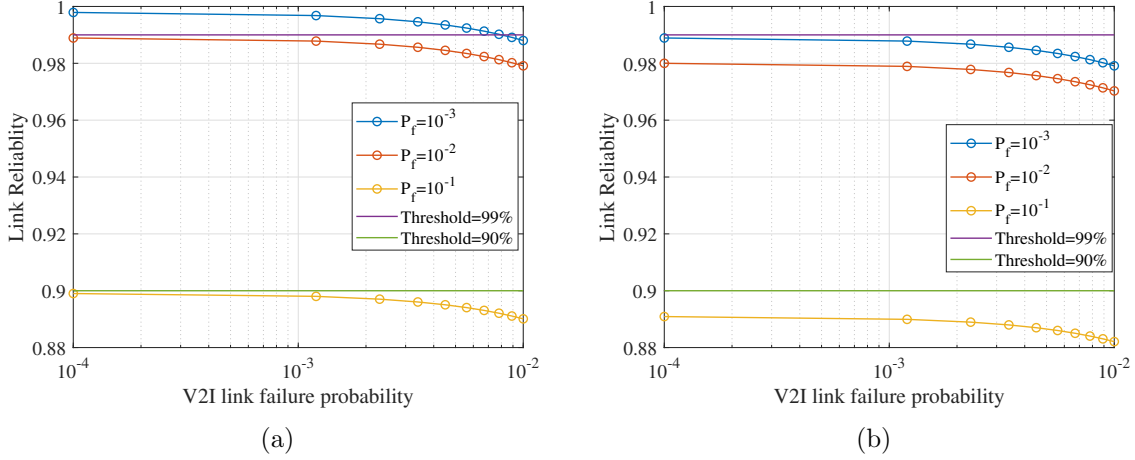


Figure 6.11: Link Reliability for V2I link for $P_V^F = P_{RSU}^F = P_{ONU}^F = 10^{-6}$: a) $P_{cong}^F = 10^{-3}$ and b) $P_{cong}^F = 10^{-2}$.

cut failure 10^{-2} as the network congestion increases from 10^{-6} to 10^{-2} . Furthermore, for $P_f = 10^{-3}$, it can be observed that as the network congestion increases to 10^{-2} , the reliability requirement of T-CONT₂ traffic of the V2I link is not met even at 10^{-4} V2I link failure probability. Similarly, for $P_f = 10^{-1}$, the reliability requirement cannot be met for any of the T-CONTs.

6.8 Conclusions

In this chapter, we have proposed a framework to improve the performance of FiWi-assisted vehicular communication networks. Specifically, we proposed an ML-based T-CONT priority assignment wavelength allocation algorithm to meet the stringent requirements of 6G vehicular traffic. In order to facilitate the above, a mapping between the various kinds of vehicular data traffic and their 6G KPIs, namely throughput, delay, and reliability, is studied. Thereafter, we classified the V2I traffic among four classes based on their KPI requirements. Each class of traffic is assigned to a T-CONT for wavelength allocation at each ONU-RSU. By exploiting vehicular traffic predictions through ML, a framework is proposed to allocate the wavelength to the ONU-RSUs. The efficiency of

the proposed ML-based T-CONT priority assignment wavelength allocation algorithm is compared with the other approaches, namely equal T-CONT allocation and random wavelength allocation algorithm in terms of e2e delay, throughput, and reliability. Through simulations, it has been shown that by utilizing the proposed ML-based T-CONT priority assignment wavelength allocation algorithm, performance in terms of delay, throughput, and reliability is achieved within the standardized ITS requirements. Moreover, the key deployment challenges of the proposed scheme are also discussed in this chapter.

Chapter 7

Priority Based V2V Data Offloading Scheme for FiWi Based Vehicular Network Using Reinforcement Learning

7.1 Introduction

The previous chapter focuses on proposing a V2I data offloading scheme for maintaining QoS requirements of the user. However, all the data in vehicular data traffic need not be offloaded to the infrastructure, and some of the data could be locally computed or offloaded to the vehicles. In this chapter, we focus on the V2V application for vehicular data traffic. Specifically, we propose a RL based DDQN scheme that utilizes energy and delay of the offloading process to choose the cluster head for the V2V data offloading scheme.

7.2 Contributions

It is imperative to consider energy along with safety and security as one of the critical parameters for vehicular traffic. FiWi networks combine the advantages of fiber with wireless network and are therefore a potential candidate technology for the future 6G

networks. However, to the best of the authors' knowledge, there is no literature that has investigated the aspects of energy and QoS for V2V data offloading scheme in a FiWi enhanced vehicular network. Specifically, the proposed work intends to classify the traffic based on the KPIs and improve the QoS at the vehicular user end by minimizing the latency and energy of the vehicular network. In order to do so, we propose a RL based DDQN scheme that chooses the cluster-head for V2V data offloading scheme. We also study the trade-off between energy and latency of the vehicular network. Further, the energy and latency minimization problem is solved using an exhaustive search to validate the performance of the RL algorithm.

7.3 Network Model

We consider a FiWi network consisting of a next generation passive optical network 2 (NG-PON2) as the back-end and vehicular network as the front-end as shown in Fig. 7.1. The fiber backhaul network provides high bandwidth and, therefore, is one of the popular backhaul solutions [146]. In the United States, 90% of the wired backhaul network consists of fiber backhaul network followed by copper-based network [147]. The fiber backhaul is expected to grow to 40.2% of macro cell sites by 2025 [146]. Thus, the considered network consists of a fiber backhaul network at the backend with a vehicular network at the front end. The NG-PON2 network consists of an OLT located at the central office. The transmit power of the OLT is split among the ONUs using a passive splitter. The ONU contains five T-CONTs, namely T-CONT₁, T-CONT₂, T-CONT₃, T-CONT₄, and T-CONT₅, with following order of priority: T-CONT₁ > T-CONT₂ > T-CONT₃ > T-CONT₄ > T-CONT₅. T-CONT₁ has the highest priority and is considered to be reserved for background traffic [53]. Thereafter, T-CONT₂ is assigned higher priority data, i.e., the data that requires lower latency as well as high throughput and reliability, whereas the lowest priority data is assigned to T-CONT₅. The RSUs are collocated with the ONUs

and connect wirelessly to the vehicles [146], [148]. Each vehicle is assumed to generate any of the four kinds of traffic, as described in subsequent sections. These traffics are assigned to the T-CONTs based on their priority. The assignment of traffic to different T-CONTs is defined in detail in the subsequent sections. This work aims to improve the QoS of the vehicular network. In order to do so, we focus on the performance improvement for the high-priority T-CONT₂ data traffic. This traffic is offloaded locally within the cluster, i.e., the group of vehicles connected to the same RSU, whereas the other types of traffic are offloaded to the infrastructure. The vehicles have limited computation capacity; thus, there would be more computation resources available with the infrastructure for the other kinds of traffic. However, the T-CONT₂ vehicular data traffic has the highest priority and has the least latency tolerance requirements; hence, in this work, we have assumed the V2V offloading scenario for T-CONT₂ data traffic, and for the other T-CONTs, the data will be offloaded to the infrastructure. For V2V offloading, a vehicle is selected among the group of vehicles generating T-CONT₂ data in the cluster as the cluster-head, which computes the T-CONT₂ tasks for all the vehicles in the cluster. This work proposes a method for selecting the optimal cluster head by minimizing the energy and latency of the vehicular network and maximizing the network's throughput and reliability.

7.3.1 Communication Model

In this subsection, we define the communication model between task vehicles and the cluster-head. The wireless channel between cluster-head and task vehicles is considered to be static during each time slot [68]. The transmission rate between cluster-head and task vehicle is calculated as,

$$R_{n,k} = B_{n,k} \log_2 (1 + \Gamma_{n,k}), \quad (7.1)$$

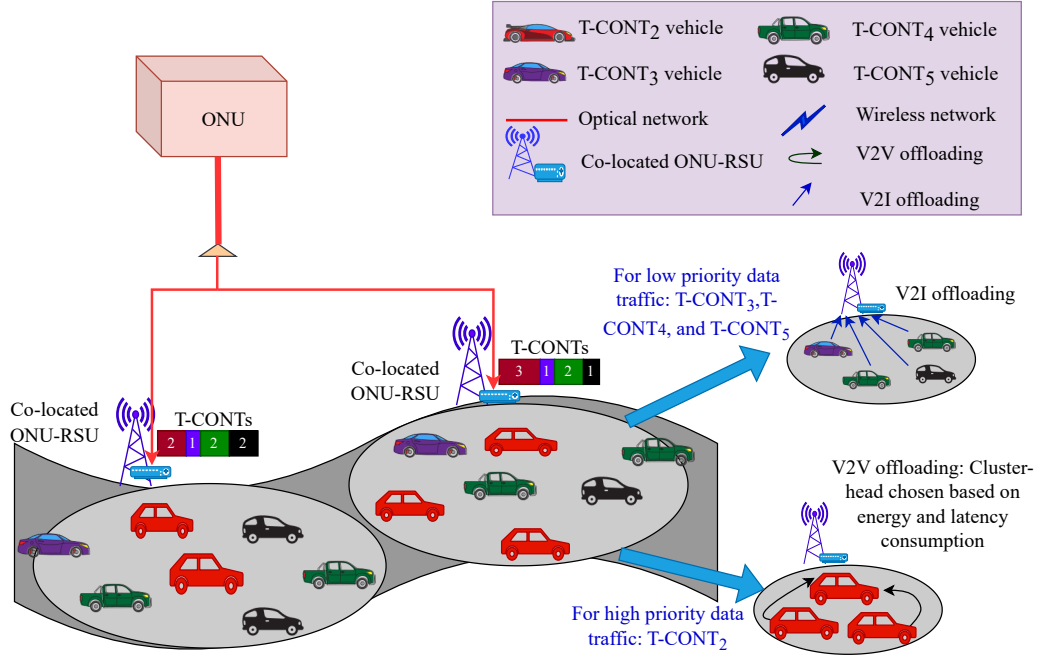


Figure 7.1: System model for V2V offloading assisted V2I network.

where $B_{n,k}$ is the allocated bandwidth to the V2V channel between task vehicle V_n and cluster-head vehicle V_k , $\Gamma_{n,k}$ represents the signal-to-noise ratio (SNR) of the wireless channel, which is calculated as,

$$\Gamma_{n,k} = \frac{P_t d_{n,k}^{-\alpha} h_{n,k}^2}{N_0}, \quad (7.2)$$

where P_t represents the transmission power of the vehicular tasks, $d_{n,k}$ is the distance between task vehicle V_n and cluster-head vehicle V_k , α denotes the path loss exponent, $h_{n,k}$ represents the channel gain, N_0 is the power of Gaussian white noise.

7.3.2 Computation Model

The amount of tasks leaving V_n 's task offloading queue at time slot t , i.e., $W_n^{off}(t)$, can be calculated as [68],

$$W_n^{off}(t) = \min \{Q_n^{off}(t), \tau R_{n,k}(t)\}, \quad (7.3)$$

where $Q_n^{off}(t)$ is the size of the offloading queue at t^{th} time slot and τ is the latency threshold for the vehicular tasks [67]. Similarly, the amount of data transmitted by vehicle S_k at time slot t as feedback after the processing of the vehicular tasks is expressed as [68],

$$W_{n,k}^{bac}(t) = \min\{G_{n,k}^{bac}(t), \tau R_{n,k}(t)\}, \quad (7.4)$$

where $G_{n,k}^{bac}(t)$ is the result feedback queue sent by the cluster-head vehicle V_k after computation of the task at t^{th} time slot.

The amount of vehicular tasks to be offloaded might require some local computing at V_n in the t^{th} slot and can be calculated as [68],

$$W_n^{loc}(t) = \min\left\{Q_n^{loc}(t), \frac{\tau f_n(t)}{\lambda_n}\right\}, \quad (7.5)$$

where $Q_n^{loc}(t)$ is the queue of the tasks to be offloaded at t^{th} time slot, $f_n(t)$ denotes the assigned CPU frequency at V_n at t^{th} time slot and λ_n represents a constant that indicates the required computational density (cycles/bit) for a task. The amount of tasks processed by edge computing at S_k in time slot t can be calculated as,

$$W_{n,k}^{com}(t) = \min\left\{G_{n,k}^{com}(t), \frac{t f_{n,k}(t)}{\lambda_n}\right\}, \quad (7.6)$$

where $f_{n,k}(t)$ is the assigned computing resource for executing offloaded tasks within slot t , $G_{n,k}^{com}(t)$ is the stored offloaded tasks at V_n at t^{th} time slot.

7.3.3 Energy Consumption Model

The energy consumption in the vehicular network consists of the following components [68]:

1. The energy consumption required for the processing of tasks that will be offloaded

for computation is expressed as,

$$E^{loc}(t) = \kappa |f_n(t)|^3 \min \left\{ \frac{\lambda Q_n^{loc}(t)}{f_n(t)}, \tau \right\}, \quad (7.7)$$

where κ is the computation power parameter. The $\min\{.\}$ operator in (7.7) assures that the time taken to process the task is within the latency threshold requirement.

2. The energy consumed by the task ϕ_n during task offloading process to vehicle V_n is given as,

$$E_n^{off}(t) = P_t \min \left\{ \frac{Q_n^{off}(t)}{R_{n,k}(t)}, \tau \right\}. \quad (7.8)$$

3. The energy consumed during the computation of task ϕ_n at the cluster-head V_n is given as,

$$E_n^{com}(t) = \kappa |f_n(t)|^3 \min \left\{ \frac{\lambda G_{n,k}^{com}(t)}{f_n(t)}, \tau \right\}. \quad (7.9)$$

4. The energy consumed while sending the task ϕ_n result feedback can be calculated as,

$$E_n^{bac}(t) = P_t \min \left\{ \frac{G_{n,k}^{bac}(t)}{R_{n,k}(t)}, \tau \right\}. \quad (7.10)$$

7.4 Problem Formulation

The objective of this work is to minimize the energy consumption of the vehicular network while maintaining the QoS. As latency is one of the critical QoS parameters of the network, thus we aim to minimize both the energy consumption and latency of the network. The objective problem thus formulated is given as,

$$\min_{c_k^n, f_k^n} \frac{1}{T_{total}} \sum_{t=1}^{T_{total}} [\mathbb{1}(\beta_n = \beta^{T_2}) \mathcal{D}_k^n(t) + \eta E_k^n(t)], \quad (7.11a)$$

$$s.t. \ E_k^n(t) = E^{loc}(t) + c_k^n(t)[E_n^{off}(t) + E_n^{com}(t) + E_n^{bac}(t)], \quad (7.11b)$$

$$\mathcal{D}_k^n(t) = \mathcal{D}^{loc}(t) + c_k^n(t)[\mathcal{D}_n^{off}(t) + \mathcal{D}_n^{com}(t) + \mathcal{D}_n^{bac}(t)], \quad (7.11c)$$

$$c_k^n(t) = \{0, 1\}, \quad (7.11d)$$

$$\sum_k c_k^n(t) = 1, \quad (7.11e)$$

$$\sum_k f_k^n \leq \Delta, \quad (7.11f)$$

$$\sum_k B_{n,k} \leq B_f, \quad (7.11g)$$

where $\mathbb{1}(\cdot)$ is an indicator function, $\beta_n = \beta_n^{T_2}$ denotes that the tasks ϕ_n belongs to T-CONT₂ traffic, η is the trade-off factor between energy and latency, $c_k^n(t)$ denotes the offloading of task ϕ_n to k^{th} vehicle at t^{th} time slot, $D_k^n(t)$ is the latency for task ϕ_n traffic, $D^{loc}(t)$ is the latency in the processing of tasks that will be offloaded to the vehicular infrastructure or cluster-head for computation at t^{th} time slot, $D_n^{off}(t)$ is the latency due to offloading the tasks at t^{th} time slot, $D_n^{com}(t)$ is the computational latency of the tasks at the cluster-head at t^{th} time slot, $D_n^{bac}(t)$ is the latency due to feedback of the processed tasks at t^{th} time slot. Δ is the available CPU clock speed, and B_f is the available bandwidth resources at the vehicles. The optimization problem in (7.11a) minimizes the average energy consumption and the latency of task ϕ_n at each time slot. The constraint in (7.11b) signifies the energy consumed by the task. The energy consumption consists of two parts: a) the energy consumption for the tasks of T-CONT₂ traffic, i.e., V2V offloading and b) the energy consumption for the tasks offloaded to V2I link for computation. Similarly, the latency for the task ϕ_n also consists of two parts depending on the type of offloading and is shown in constraint (7.11c). The constraint in (7.11d) indicates whether the task ϕ_n is offloaded. If there is a V2V offloading of task ϕ_n from vehicle V_n to vehicle V_k , c_k^n is assigned value 1, else $c_k^n = 0$. As the task can be offloaded to only one of the vehicles in the cluster-head, thus $\sum_k c_k^n = 1$. This is also shown in constraint (7.11e). The constraint on the CPU clock speed and the bandwidth available at each vehicle is specified in (7.11f) and (7.11g), respectively. In this work, available bandwidth from the

backhaul fiber network is divided equally among all the ONU-RSUs. This bandwidth at the ONU-RSUs is further equally divided for vehicular tasks in the cluster-head.

7.5 Solution Methodology

This section of the work focuses on deep learning methods to solve the optimization problem (7.11). It is assumed that within the cluster a few of the vehicles generate T-CONT₂ traffic that has to be offloaded to a particular cluster-head within a time slot. A remote cloud determines the cluster-head and corresponding service price for an offloading task. Therefore, this task offloading problem is a sequential decision-making problem under dynamic vehicular environment. Due to the mobility, the channel conditions between the vehicles are time-variant, and thus, the computational resources at the vehicles are also time-variant. Thus, we can reformulate the problem as a Markov decision process as shown in [68] whose dynamics are unknown to the remote cloud server. In order to solve the above problem, we utilized value based deep reinforcement learning (DRL) algorithm, namely DDQN. The DDQN is utilized to reduce the overestimation errors of Q -network as it decomposes the max operation into action selection and evaluation. This section demonstrates the state space, action space, reward function, policy, and reward function for the proposed problem.

7.5.1 State Space

It is assumed that the remote server initially collects the information about the data size of the tasks to be offloaded from the task vehicles. The amount of CPU clock speed available at the cluster-head is assumed to be constant. The CPU clock speed required by the tasks will be calculated as a function of the offloading tasks available at the cluster-head vehicle.

The state space, S at t^{th} slot is [66],

$$S_t = [d^1(t), d^2(t), \dots, d^{N_2}(t)],$$

where N_2 is the available set of vehicles generating T-CONT₂ traffic, $d^i(t)$ is the data size of the offloading task ϕ_i at t^{th} time slot.

7.5.2 Action Space

Depending on the state of the network at t^{th} slot, the action space of the network is decided, i.e., the offloading decision and the price of each task is calculated at the remote server. The action space is thus formed as [66], [69],

$$A_t = [c_k^1(t), c_k^2(t), \dots, c_k^N(t), p_1(t), p_2(t), \dots, p_N(t)], \quad (7.12)$$

where $c_k^i(t)$ is a binary variable that represents whether i^{th} vehicle has a task to be offloaded to k^{th} vehicle and $p_i(t)$ is the price for i^{th} vehicle at t^{th} time slot. The price for the task is defined in detail in the later subsection.

7.5.3 Reward Function

According to the state space and actions taken during the t^{th} time slot, a reward is assigned which is given as [66], [69],

$$R(S_t, A_t) = - \sum_{n=1}^N [\mathcal{D}_k^n(t) + \eta E_k^n(t)]. \quad (7.13)$$

The optimization problem (7.11) minimizes the energy of the network while keeping the latency within the tolerable limit. Thus the mean reward is given as,

$$R = -\frac{1}{T_{total}} \sum_{t=0}^{T_{total}-1} \sum_{n=1}^N [\mathcal{D}_k^n(t) + \eta E_k^n(t)]. \quad (7.14)$$

7.5.4 Price Model

At each vehicle, there may be V2I and V2V offloading tasks at the task vehicles to be executed at the same time. Considering the limited on-board computational capability at the task vehicle, it may not be able to ensure that enough computational resources are allocated to both types of tasks. Therefore, the computational resource allocation should first guarantee that the high-priority tasks are completed within the latency threshold. As T-CONT₂ data traffic is of the highest priority, therefore the T-CONT₂ tasks should be within the tolerable latency limit as defined in Table 6.1. Thus, we introduce a logarithmic function to define a latency-based utility function for the task, ϕ_n as [66], [69], [149],

$$\mathcal{U}_n^{T_2} = \begin{cases} \log(1 + \tau_n - t_n), & t_n \leq \tau_n \\ -\Gamma, & \text{otherwise,} \end{cases} \quad (7.15)$$

where, τ_n is the threshold latency of T-CONT₂, t_n is the latency of the T-CONT₂ tasks, Γ is the a non-negative constant. As the T-CONT₂ tasks are of high priority, thus they should be completed within the threshold latency of 5 msec [13]. This is incorporated in the utility function as the utility of task ϕ_n is assigned a negative value if the latency for ϕ_n is more than the latency threshold τ_n . This signifies a negative penalty is assigned if the latency for ϕ_n is more than τ_n . In case the latency is less than the latency threshold, the utility is assigned a positive value.

Considering that there are L_n local tasks at cluster-head vehicle V_k and the computation size and the latency threshold of each local task are denoted as C_l and τ_l , respectively.

Then, the minimum CPU clock speed required for local tasks is given as $F_{min}^k = \sum_{l=1}^{L_n} C_l \tau_l$. If a cluster-head vehicle does not receive any V2V task offloading requests, then it will allocate all of its computing resources to local tasks. The maximum resource that can be allocated to the local tasks is given as $F^k = \sum_{l=1}^L C_l \theta_k \tau_l$, where $\theta_k = F_{min}^k / F^k$. It can be observed that the range of CPU clock speed allocated to the local tasks is $[F_{min}^k, F^k]$. The variable θ denotes the ratio of F_{min}^k to the computing resources reserved for local tasks, the range of θ can be given as $[\theta_k, 1]$ [66].

Once a vehicle decides to accept an offloading request from another vehicle and allocates frequency f_n to an offloading task ϕ_n , the utility of local tasks changes from $\mathcal{U}_{T_2}^k(\theta_k)$ to $\mathcal{U}_{T_2}^k(\theta'_k)$, and the price $p_n C_n$ paid for task ϕ_n should satisfy,

$$p_n C_n = \mathcal{U}_k^{loc}(\theta_k) - \mathcal{U}_k^{loc}(\theta'_k), \quad (7.16)$$

$$\mathcal{U}_k^{loc}(\theta_k) = \sum_{l=1}^L \log(1 + \tau_n - \theta_k \tau_n), \quad (7.17)$$

i.e., the service price of an offloading task should compensate for the loss of the utility of local tasks. After given the price $p_n C_n$, the CPU clock speed allocated to task ϕ_n is calculated. The price is predicted using the DDQN algorithm based on the current policy. Depending on the price and the local utility of the vehicle, the new local utility is calculated using (17). Finally, the allocated CPU clock speed allocated to the task offloaded by n^{th} vehicle is calculated as follows:

$$f_k^n = \frac{\sum_n(\phi_n) \left[\Delta - \left(F_k - \frac{F_k^{min}}{\theta'_k} \right) \right]}{\phi_n}, \quad (7.18)$$

where ϕ_n is the amount of data offloaded from vehicle n to cluster-head, Δ is the available CPU cycle speed, θ'_k is the ratio of minimum CPU clock speed for the local tasks to the total CPU clock speed available for local tasks if the cluster head decides to accept the V2V offloading request from vehicle n . The range of the unit price of task ϕ_n is

$[0, \mathcal{U}_k^{T_2}(\theta_k)/C_n]$. As a result, if an offloading task requires more computing resources, the task vehicle should pay V_k a higher price.

7.5.5 Policy And Value Function

A policy in reinforcement learning is defined as the strategy of actions for a long-term return [68]. In DDQN, a stochastic policy is also denoted by the probability distribution of the action state, given that the state space is evaluated. The aim of the proposed algorithm is to determine a policy, $\pi(A|S)$, that maximizes the expected return. As the current action can affect the future returns, the action-value function $Q_\pi(S, A)$ is defined as the expected discounted return of a trajectory starting at time 0 with state S and selecting action A , which is given as,

$$Q_\pi(S, A) = \mathbb{E}_{\mu\tilde{\pi}} \sum_{t=0}^{T_{total}-1} \gamma_{DF} R_t | S_0 = S, A_0 = A, \quad (7.19)$$

where R_t is the reward function also denoted as $R(S_t, A_t)$, $\gamma_{DF} \in (0, 1)$ is discount factor, μ denotes the state-action trajectory $\{S_0, A_0, S_1, A_1, \dots, S_{T_{total}-1}, A_{T_{total}-1}, S_{T_{total}}\}$.

Similarly, the state-value function $V_\pi(S)$, i.e., the expected discounted return starting from state S . Now, taking actions also into account, the policy π is defined as,

$$V_\pi(S) = \mathbb{E}_{\mu\tilde{\pi}} \sum_{t=0}^{T_{total}-1} \gamma_{DF} R_t | S_0 = S. \quad (7.20)$$

7.5.6 DDQN Algorithm

The DDQN algorithm is presented in Algorithm 6. There are two networks in DDQN: the online network and the target network. Both networks have the same architecture, however, they differ in terms of weight. The weights of the target network are copied from the online network periodically. The presence of two networks helps in reducing the problem of overestimation as in DQN [150], [151]. Based on the two networks, DDQN is

based on the estimation of two parameters, $\mathcal{A}$ and $\mathcal{B}$. Depending on the Q -functions of the parameters $\mathcal{A}$ and $\mathcal{B}$, an action is chosen. This is followed by choosing the next state, S' and the reward, R_t . Finally, depending on the action and next state, the estimators $\mathcal{A}$ and $\mathcal{B}$ are updated until convergence. The DDQN algorithm has an advantage over DQN algorithm as it reduces the overestimation error of DQN algorithm. In the basic DQN, the updated Q -function is given as [152],

$$Q_{\pi}^{DQN}(S, A) \leftarrow Q_{\pi}^{DQN}(S, A) + \delta_r[R_t + \gamma_{DF} \max_{A_{t+1}} Q_{\pi}(S_{t+1}, A^*)] - Q_{\pi}^A(S_t, A_t), \quad (7.21)$$

where A^* is the best action A with maximum Q -value of the next state, δ_r is the learning rate, i.e., a hyper-parameter for controlling the speed of convergence during the updates, γ_{DF} is the discount factor that weights the importance of future rewards [152]. The policy is further improved in DDQN to overcome the overestimation error as [153],

$$Q_{\pi}^{DDQN}(S, A) \leftarrow Q_{\pi}^{DDQN}(S_t, A_t) + \delta_r[R_t + \gamma_{DF} Q'_{\pi}(S_{t+1}, A^*)] - Q^A(S_t, A_t), \quad (7.22)$$

where $Q'_{\pi}(S_{t+1}, A^*)$ is the estimated or expected Q -value. It is interesting to observe that in order to reduce the overestimation, the DDQN algorithm replaces the weights of the second network with the weights of the target network. This minimum change in DQN benefits in reducing the overestimation while keeping the rest of the DQN algorithm intact for a fair comparison and with minimal computational overhead [152].

7.5.6.1 Training Process

At each step, we calculate the action using the online network. We select the action using the ϵ -Greedy policy. In the ϵ -Greedy policy, we select the action randomly using the probability ϵ , and the action with maximum Q -value is selected with probability $1 - \epsilon$. We use this policy so that the agent can keep exploring while also exploiting its current learned policy so that it may find some better policy in the long run. After selecting the

action, an immediate reward will be given, and the action will be shifted to the next state. The value of ϵ is slowly decreased with epochs, so that the agent can exploit the learned policy more as compared to exploring. The value ϵ at t^{th} epoch is given by [150], [151]:

$$\epsilon(t) = \frac{1}{(1+t)}. \quad (7.23)$$

7.5.6.2 Loss Function

Then, we use the target network to find the action-value function corresponding to the action selected. Then the loss function is defined as:

$$L^{DDQN} = [R_t + \gamma_{DF} \max_a Q'_\pi(S_{t+1}, A^*) - Q_\pi(S_t, A_t)]^2 \quad (7.24)$$

Then, we try to minimize the loss function by finding the optimal parameters of the online network.

In DDQN, we use an experience replay buffer to enhance the stability of the training. We add the samples of the form (S_t, A_t, R_t, S_{t+1}) to the buffer at each step. During the training, a mini-batch of the buffer will be randomly sampled and used for training. This helps to reduce the correlation between the observations. Thus, it makes the algorithm more stable. Temporal difference (TD) is calculated using the Bellman equation. The Bellman equation is given as follows [66], [69]:

$$Q_\pi(S_t, A_t) = R_t + \gamma_{DF} \mathbb{E}_{S_{t+1}}[V_\pi(S_{t+1})], \quad (7.25)$$

TD error is calculated as the difference between the target Q -value and the estimated Q -value. This is used to update the weights of the online network during training.

Algorithm 6 DDQN Algorithm [153]

Initialize: $Q^{\mathcal{A}}, Q^{\mathcal{B}}$, and S .

Output: R and S' .

- 1: **Function** Update ($\mathcal{A}$)
 - 2: $\mathcal{A}^* = \arg \max_{\mathcal{A}} Q^{\mathcal{A}}(S, A)$
 - 3: $Q^{\mathcal{A}}(S', A) \leftarrow Q^{\mathcal{A}}(S, A) + \delta_r[R_t + \gamma_{DF}Q^{\mathcal{B}}(S', A^*)] - Q^{\mathcal{A}}(S, A)$
 - 4: **End Function**
 - 5: **Function** Update ($\mathcal{B}$)
 - 6: $B^* = \arg \max_{\mathcal{B}} Q^{\mathcal{B}}(S', A)$
 - 7: $Q^{\mathcal{B}}(S', A) \leftarrow Q^{\mathcal{B}}(S, A) + \delta_r[R_t + \gamma_{DF}Q^{\mathcal{A}}(S', A^*)] - Q^{\mathcal{B}}(S, A)$
 - 8: **End Function**
 - 9: repeat
 - 10: Choose action A , based on $Q^{\mathcal{A}}(S, :)$ and $Q^{\mathcal{B}}(S, :)$
 - 11: Observe the next state S' and reward R_t
 - 12: Depending on A and S' , choose either Update ($\mathcal{A}$) or Update ($\mathcal{B}$)
 - 13: $S \leftarrow S'$
 - 14: until end
-

7.5.7 Greedy Heuristics

In the greedy heuristics approach, the node is selected greedily to minimize the amount of resources required by the cluster-head vehicle for computation. This approach is elaborated in detail in [66].

7.5.8 Max-Queue Based Node Selection

In max-queue based node selection strategy, a node is selected that has highest amount of tasks in the queue. This selection is done so that minimum number of tasks have to be offloaded.

7.5.9 Random Node Selection

In random wavelength allocation algorithm, a random node is selected to offload the tasks. A similar approach was also used in [154], where the authors utilized random vehicle selection approach to compare their proposed solution for optimizing the downlink scheduling for the energy-limited vehicular network.

7.5.10 Complexity Analysis

The proposed RL-based energy and latency-aware vehicular data offloading scheme utilizes DDQN algorithm, hence the complexity of the proposed algorithm is given as $\mathcal{O}(N_{train})$ [155], where N_{train} is the number of training steps. Similarly, the complexity analysis for DDQN algorithm in terms of execution time is given by: $\mathcal{O}(N_{eval})$, where N_{eval} is the number of steps in evaluation [155]. In the case of exhaustive search the complexity will be proportional to the number of nodes in the network, thus the complexity is given as, $\mathcal{O}(N_{nodes}!)$, where N_{nodes} is the number of nodes in the network. Similarly, for random node selection, the complexity will be $\mathcal{O}(1)$. Thus, it can be concluded that as the number of nodes increases, the complexity of the exhaustive search increases. Thus, for a higher number of nodes, the proposed RL-based algorithm is less complex than an exhaustive search. Further, the complexity of random node selection is the least. However, it can be observed that the performance of random node selection is the worst.

Table 7.1: Paramters for the proposed algorithm

Parameter	Value
Learning Rate	0.001 units
Discount factor	0.99 units
Number of episodes	30 units
Number of training episodes	2000 units
Number of time stamps	30 time slots
Batch size	128 units
Number of hidden layers	2 layers
Hidden layer units	[128, 128] units
Buffer size	1000000 units
Optimizer	Adam Optimizer
Library used	PyTorch

7.6 Results

We have considered a NG-PON2 based backend network with a vehicular network at the frontend. The simulation scenario considers sixteen collocated ONU-RSUs connected to the OLT through a splitter. There are four wavelengths available at the OLT, each ONU-RSU can connect to one of the available wavelengths. For simulation, we consider a cluster of vehicles connected to a single ONU-RSU unit. The vehicles can generate four kinds of traffic, namely advanced driving, extended sensors, remote driving, and platooning. As remote driving traffic has the highest priority, it is offloaded through vehicle-to-vehicle transmissions, whereas the rest of the traffic is offloaded to the vehicular infrastructure. In the considered scenario, a cluster-head selected once remains a cluster-head until that vehicle moves out of the coverage area of ONU-RSU. Once the cluster-head navigates outside the range of RSU, the process of selecting the cluster-head starts again, and a new cluster-head is selected. Thus, in this process, the mobility of the vehicles plays into the picture for the selection of cluster-head every time the cluster-head vehicle moves out of the coverage range of ONU-RSU. Otherwise, the cluster head is selected based on the amount of resources and tasks available at the vehicles in the cluster currently. The number of arriving tasks at the vehicles follows a uniform distribution within [50, 100] kbits. The hyperparameters for the proposed RL algorithm are presented in Table 7.1. The parameters for simulations are summarized in Table 7.2. The simulation results of the considered scenario are shown in the subsequent subsections.

7.6.1 Energy and Latency Analysis

The latency for the proposed RL-based task offloading scheme is shown in Fig. 7.2. It can be observed that for the same queue size, if the available CPU clock speed (Δ) increases at the cluster-head vehicle V_k , then the computation of the tasks is faster and the latency for each task decreases. For instance, the latency of the task decreases from 6 msec to 4.2

Table 7.2: Simulation parameters

Parameter	Value
Road segment length	800m
Road segment width	50m
Number of RSUs	16
Maximum number of vehicles (110% loaded network)	29
Minimum number of vehicles (10% loaded network)	3
Δ	{10, 20} GHz
Q	{0, 50} kb
B_f	10GHz/16

msec if the available CPU clock cycle speed increases from 10 GHz to 20 GHz. Further, the effect of the residual queue (Q) on the latency performance of the V2V tasks can also be observed from Fig. 7.2. The residual queue is formed by the tasks that are not completed within the latency threshold of 5 msec. These tasks are stored in the queue until they are processed before the current tasks are generated by the vehicle. As can be observed from Fig. 7.2 that as Q increases from 0 kb to 50 kb, the latency of the tasks increases from 8.1 to 11.8 msec for 10 GHz CPU clock speed. Moreover, it is interesting to note that for a latency threshold of 5 msec, a network with $\Delta = 10$ GHz can accommodate a 35% and 50% network load for a queue size of 50 kb and 0 kb, respectively. However, if the Δ is increased to 20 GHz then for a latency threshold on 5 msec, the network can accommodate 70% and 90% of the load. This signifies that for the same latency threshold, if the CPU clock speed is doubled, then the load tolerance of the network also doubles. This is because at CPU clock speed of 10 GHz and $Q = 50$ kb, 5 msec latency is achieved at 0.35% loaded network, however, if we double the CPU clock speed to 20 GHz, 5 msec latency is achieved at 0.75 normalized offered load. Thus, for the same latency threshold, on doubling the CPU clock speed, the accommodation of load also doubles.

Fig. 7.3 shows the energy consumption of the network with an increase in normalized load. It can be observed that the energy consumption of tasks decreases with an increase in the normalized offered load. This is because as the normalized load increases, the frequency allocated to the tasks decreases which decreases the overall energy consumption.

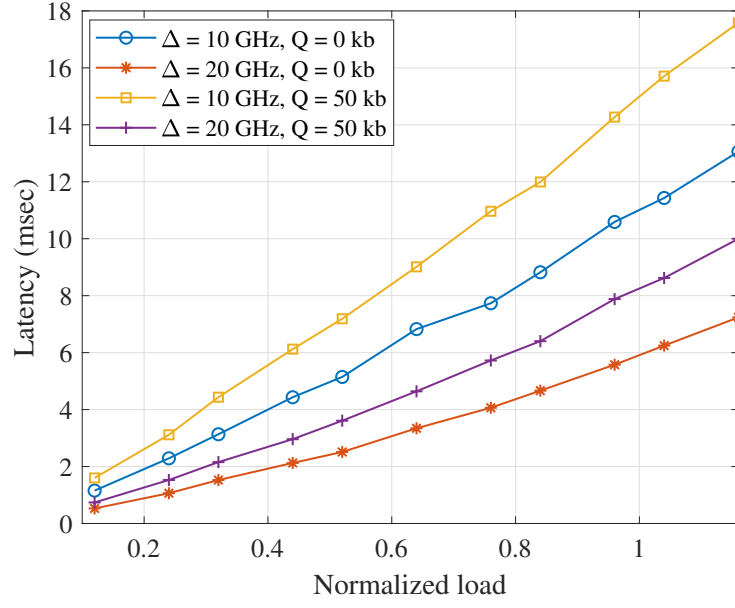


Figure 7.2: Latency vs normalized offered load for V2V link for $\Delta = \{10, 20\}$ GHz and $Q = \{0, 50\}$ kb.

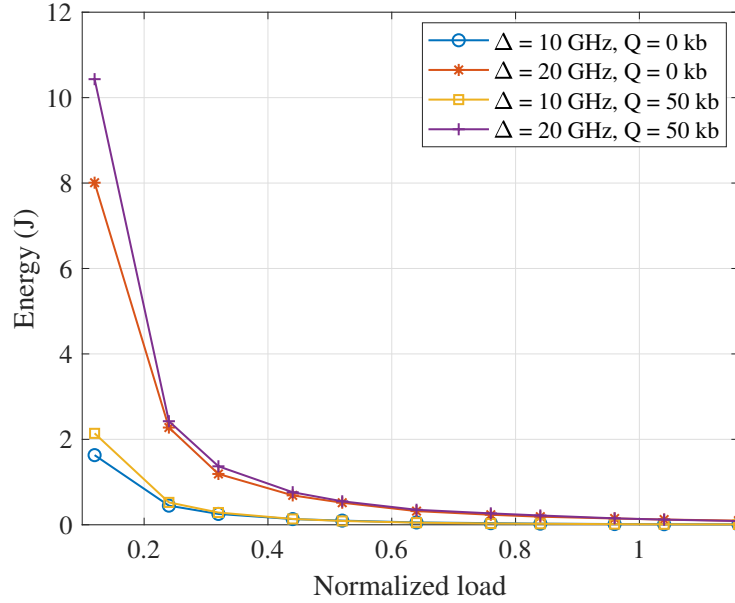


Figure 7.3: Energy vs normalized offered load for V2V link for $\Delta = \{10, 20\}$ GHz and $Q = \{0, 50\}$ kb.

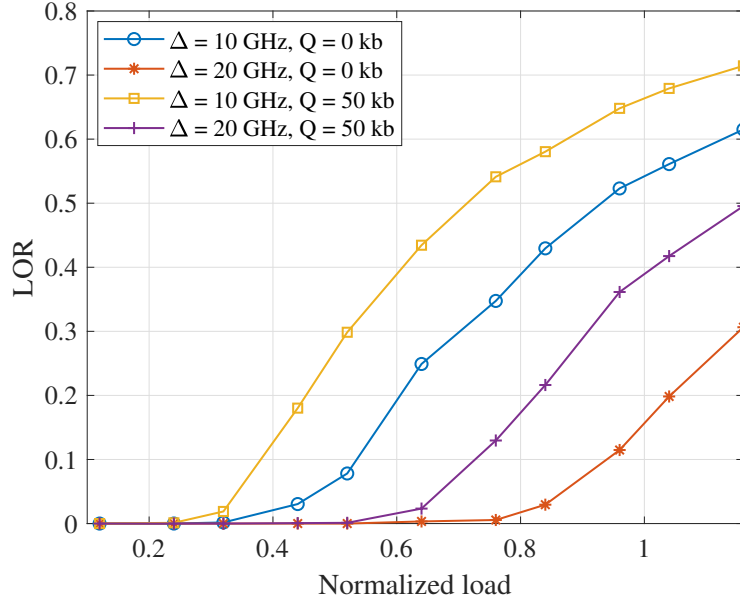


Figure 7.4: Latency outage rate vs normalized offered load for V2V link for $\Delta = \{10, 20\}$ GHz and $Q = \{0, 50\}$ kb.

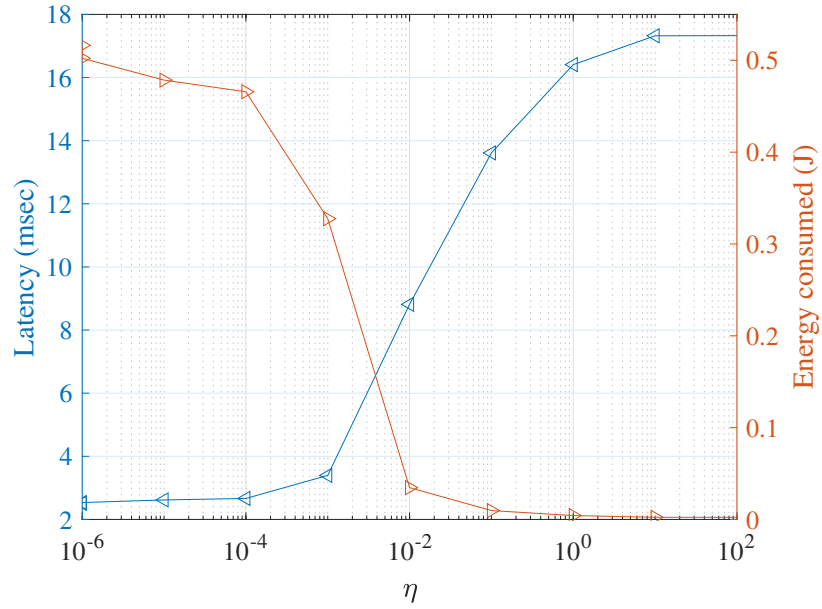


Figure 7.5: Latency and energy consumption for different η values for 70% loaded network.

This impact can also be observed from Fig. 7.3, where the increase in Δ from 10 GHz to 20 GHz, results in an increase in the energy consumption of the network by 0.8 J for 50% loaded network. Moreover, as the Q increases from 0 to 50 kb, there is a slight increase in energy consumption for low load, however, for high load networks there is no significant change in the energy consumption of the network.

Fig. 7.4 shows the impact of latency outage rate (LOR) over the normalized offered load. It can be observed that as the normalized load increases, the LOR of the network also increases. This is because as the normalized load of the network increases, the number of tasks having latency more than the latency threshold increases. Similarly, with the increase in Q , the number of tasks reaching the destination within the given latency threshold also decreases, thus the LOR of the tasks increases from 40% to 55% for a normalized offered load of 80%. Moreover, with the increase in Δ from 10 GHz to 20 GHz, the LOR decreases from 40% to 2% for $Q = 0$ kb.

Fig. 7.5 shows the variation of energy vs latency for variation of energy and latency trade-off factor, η for 70% loaded network. It can be observed that as η increases, there is more focus on energy in the problem ($P1$). Hence, energy of the network decreases with the increase in η . Similarly, as η decreases, the focus is more towards the latency and therefore, latency decreases as η decreases. Further, it is interesting to observe that on increasing η beyond 10^1 , there is no significant change in the energy consumption and latency of the tasks. A similar effect can be observed with the decreasing in η below 10^{-5} . Furthermore, it can also be observed that the energy and latency crossover is happening at $\eta = 3 \times 10^{-3}$. This is because the energy of the tasks is calculated in Joules and the latency of the tasks is computed in milliseconds, thus, in order to have equal weightage to energy and latency the operator can choose η close to 10^{-3} . Further, depending on the energy and latency requirement of the operator the value of η can be chosen.

The variation of energy and latency in comparison to other schemes is shown in Fig. 7.6 for 70% loaded network. We have compared the proposed RL-based scheme with greedy

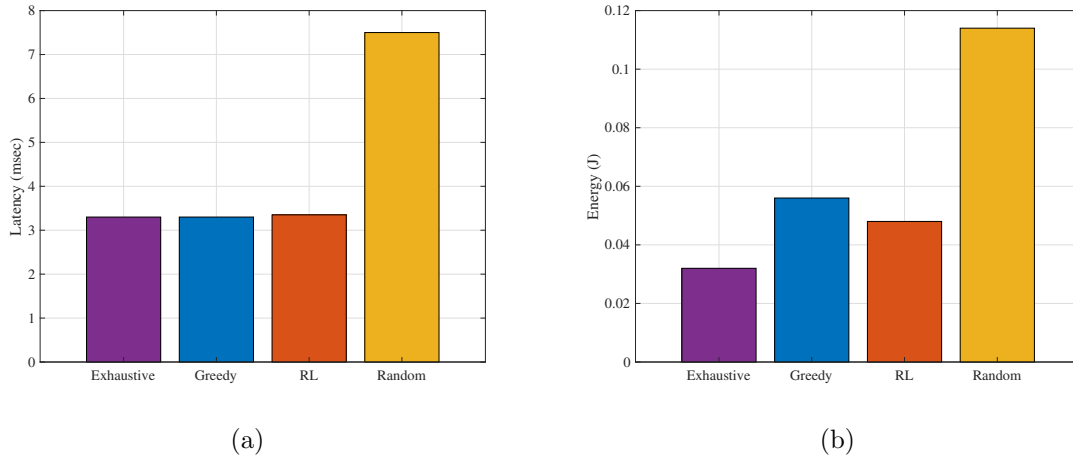


Figure 7.6: a) Latency and b) energy without queue for various schemes.

method and other non-learning based method such as random node selection scheme. It can be observed that the proposed RL scheme performs similar to greedy and exhaustive search in terms of latency, however, in terms of energy consumption, the proposed scheme outperforms the random node selection method and greedy heuristic. The exhaustive search gives the optimal cluster-head selection method, however as discussed earlier the complexity of the exhaustive search is highest. The performance of the proposed algorithm is close to the exhaustive search algorithm, i.e., closer to the optimal solution in terms of both energy and latency. Moreover, the exhaustive search performs better than the proposed RL-based method. A similar comparison of energy and latency with other schemes is shown in for a 50 kb queue in Fig. 7.7 for 70% loaded network. It can be observed that random node selection scheme performs the worst followed by maximum queue based node selection scheme, greedy heuristic, proposed RL-based scheme, and exhaustive search. The latency performance of the proposed RL-based scheme is close to the exhaustive search. However, for the energy consumption scheme, the exhaustive search performs better than the proposed RL-based scheme. Thus, it can be concluded that the proposed RL-based scheme is sub-optimal for energy and latency-aware V2V networks.

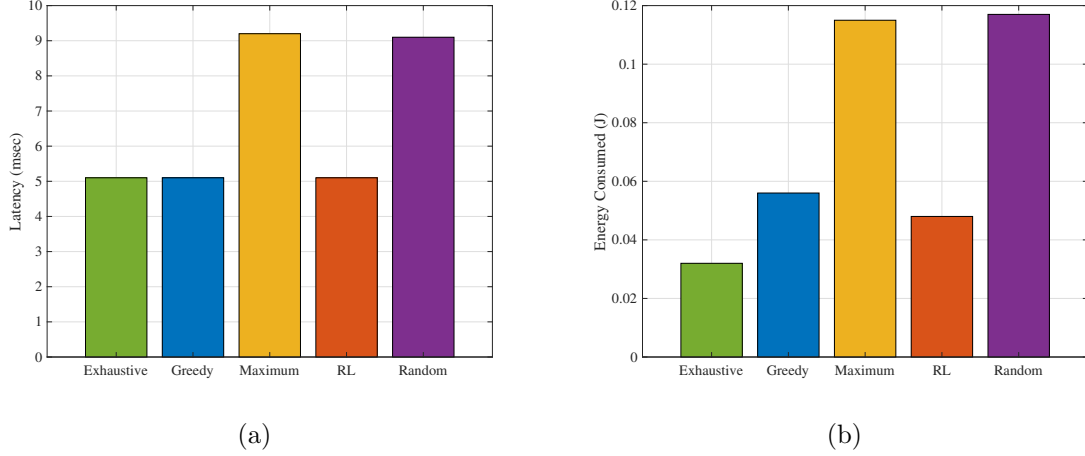


Figure 7.7: a) Latency and b) energy for $Q = 50$ kb for various schemes.

7.6.2 Throughput Analysis

This subsection presents the throughput analysis of V2I network. It can be observed from Fig. 7.8 that as the network load increases, the throughput of the network decreases. This is because as the number of users increases, there is more congestion in the network. Further, it can also be observed that the throughput of the V2I network is not impacted by resource allocation. This is because the throughput of the V2V network depends on the bandwidth and the SNR of the vehicles. It does not depend on the amount of CPU clock speed and queue at the vehicles.

7.6.3 Reliability Analysis

In this subsection, we present the link reliability for V2V link and compare it with V2I link. The e2e link reliability for a FiWi based V2I network is calculated as,

$$P_I^S = P_{V2I}^S \cdot P_V^S \cdot P_{RSU}^S \cdot P_{ONU-OLT}^S, \quad (7.26)$$

where P_{V2I}^S , P_V^S , P_{RSU}^S is the V2I link reliability, vehicle equipment reliability, and the reliability of RSU, respectively. $P_{ONU-OLT}^S$ is the probability of successful transmission

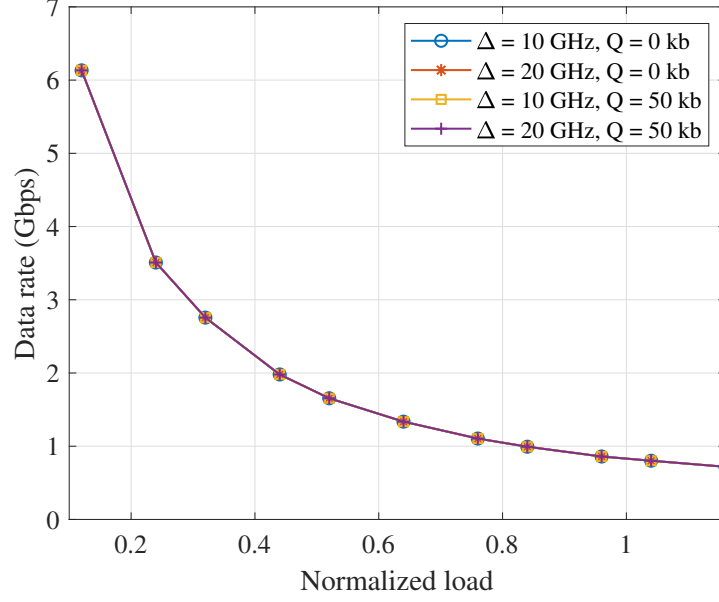


Figure 7.8: Throughput analysis for V2I link.

from ONU to OLT. The failure of V2I transmission can be denoted as,

$$P_I^F = 1 - P_I^S = 1 - (1 - P_{V2I}^F)(1 - P_V^F)(1 - P_{RSU}^F)(1 - P_{ONU-OLT}^F), \quad (7.27)$$

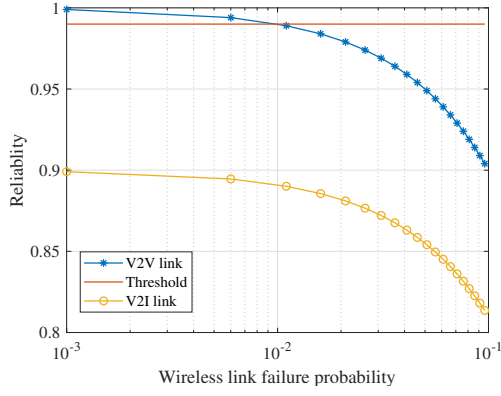
where P_{V2I}^F , P_V^F , P_{RSU}^F is the probability of failure of V2I link, vehicle equipment, and RSU, respectively. $P_{ONU-OLT}^F$ is the probability of failure of transmission from ONU to OLT which is given by:

$$P_{ONU-OLT}^F = 1 - (1 - P_{ONU}^F)(1 - P_C^F), \quad (7.28)$$

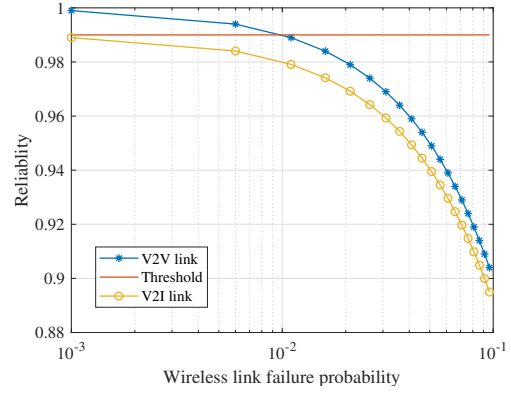
where P_{ONU}^F denotes the probability of failure of ONU and P_C^F is the probability of fiber cut. Thus, reliability for V2I transmission is given as,

$$P_I^S = 1 - P_I^F = (1 - P_{V2I}^F)(1 - P_V^F)(1 - P_{RSU}^F)(1 - P_{ONU}^F)(1 - P_C^F). \quad (7.29)$$

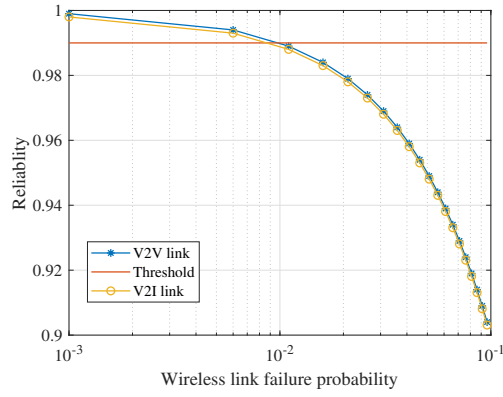
Similarly, the link reliability for the V2V link is calculated as,



(a) $P_f = 10^{-1}$



(b) $P_f = 10^{-2}$



(c) $P_f = 10^{-3}$

Figure 7.9: Reliability analysis with respect to wireless link failure (V2V/V2I Link) for fiber cut probability of: (a) $P_f = 10^{-1}$, (b) $P_f = 10^{-2}$, and (c) $P_f = 10^{-3}$.

$$P_V^S = P_{V2V}^S P_V^S, \quad (7.30)$$

where P_{V2V}^S is the V2V link reliability.

It is interesting to note that for the fiber cut failure does not have any impact on the link reliability of V2V transmission. Fig. 7.9 shows the comparison of link reliability for different wireless (V2V/V2I) link failure probabilities for different fiber cut failure probabilities, $P_f = \{10^{-1}, 10^{-2}, 10^{-3}\}$. It can be observed that as the wireless link failure probabilities increases, the reliability of the network decreases. Further, the V2I transmissions are only suitable if the fiber cut probability is low, i.e., $P_f < 10^{-2}$. Moreover, it can also be observed that the link reliability for V2I link is close to that of V2V link for low fiber cut failure of 10^{-3} . Further, in order to meet the reliability requirement of T-CONT₂, the wireless link failure probability must be less than 10^{-2} .

7.7 Conclusions

In this chapter, we proposed an energy and latency-aware V2V data offloading scheme for FiWi-based vehicular networks. Specifically, we utilized an NG-PON2-based back-end network with a vehicular network at the front end. To do so, we classified vehicular traffic into four categories according to their KPIs and proposed a V2V data offloading scheme for high-priority vehicular data. In order to ensure that the network is energy efficient and has improved QoS, we propose a reinforcement learning-based DDQN scheme for choosing the cluster head for V2V communication. The performance of the proposed algorithm is compared with the non-RL-based approach, such as random and max-queue-based cluster-head selection. Further, we also compared the results of the proposed algorithm with greedy heuristics and exhaustive search to validate the performance. The simulation results demonstrate the efficiency of the proposed algorithm in terms of energy, latency, throughput, and reliability.

Part IV

Emergency Path Planning For Safe-driving in Transportation Metaverse (TransVerse)

Chapter 8

Emergency Path Planning for Safe-Driving in TransVerse Enabled Connected Vehicular Network

8.1 Introduction

The Metaverse is one of the most promising innovative applications for improving the ‘intelligence’ of the next-generation wireless network. The Metaverse creates a world that accommodates hundreds of millions of people who interact online through a merger of reality and virtuality. The Metaverse coexists and interacts with the real world, which is an online and shared virtual reality world. The roadmap to the Metaverse in terms of communication and networking in 6G wireless systems is depicted in [156]. This included an illustration of the Metaverse framework to meet the stringent requirements and challenges for the 6G systems. This chapter utilizes transportation Metaverse for path planning in safe-driving connected vehicular networks. Specifically, we consider a preemptive emergency situation to estimate the emergency lane maneuver and provide driving mode advice for the vehicles in the vicinity of an emergency vehicle.

8.2 Contributions

In this work, we utilize the TransVerse to balance the risk and utility of the connected vehicular network in an emergency scenario. The proposed algorithm will focus on three objectives: 1) Emergency path planning, 2) Emergency maneuvering, and 3) Driving mode advice to the vehicles in the vicinity of an emergency vehicle. In addition, with the utilization of TransVerse, the effect of driver reaction time which is in order of a few seconds can also be reduced with prior and efficient knowledge of the vehicular environment. The TransVerse for connected vehicles could help estimate the emergency lane maneuver and provide driving mode advice for the vehicles in the vicinity of emergency vehicle.

8.3 System Model

The system model for Transportation Metaverse (TransVerse) enabled connected vehicular network is shown in Fig. 8.1. When a vehicle abruptly stops in the middle of a lane, it creates an unexpected driving situation for the vehicles in the vicinity and becomes an obstacle. The vehicle behind it has a very high risk of colliding with the obstacle and is named as high collision risk vehicle (HCRV). This vehicle is directly impacted by the unexpected driving situation and needs a maneuver to bypass the obstacle. This maneuver will not only impact the current vehicle but also will impact the safety and collision probability for the vehicles in the vicinity and would depend on the position of vehicles on the other lanes. In TransVerse, the digital copies can observe the information about the vehicles, namely, location of the vehicle, speed of the vehicle, lane position, etc. Depending on this information, an emergency path is developed for the HRCV and the vehicles in the vicinity to minimize the collision risk and advise the drivers on their mode of driving to avoid collision to maximize the utility for the network.

In this work, we utilize digital twins to integrate the physical world and digital world

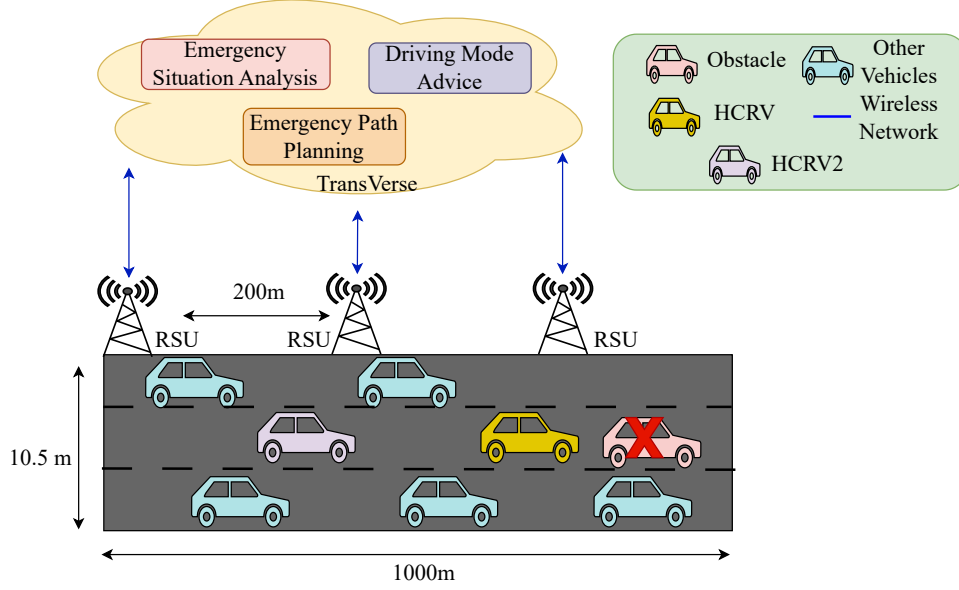


Figure 8.1: Context-aware navigation protocol for safe driving in TransVerse

entities in the network. The DT network signifies the convergence of physical and virtual networks, facilitating seamless collection of data from sensors embedded in connected vehicle networks. It is a virtual model of an object or system deliberately created to faithfully replicate a physical object. It is continuously updated using real-time data and employs simulation, machine learning, and reasoning to facilitate decision-making. An inherent constraint of the suggested method is the substantial demand for computational resources. The continuous updating of the DT network in accordance with the real-time network necessitates the presence of low-latency communication and ample computational resources within the network. Specifically, the network must continuously acquire knowledge from physical entities and adjust the network resources according to the past network states in order to meet the current network requirements. Moreover, the continuous network updates necessitate an intricately synchronized physical and digital infrastructure, which is challenging to achieve. There has been a strong interest among researchers in effectively integrating physical and digital entities.

8.3.1 Vehicular Network

We consider a road segment r_{ab} with the number of lanes L , where $L > 1$. The total number of vehicles traversing on the road is denoted by N . The vehicles are assumed to traverse in a unidirectional road segment, wherein the vehicles enter the road segment r_{ab} from a and exit from b . At a particular time slot t , the state of the i^{th} vehicle, n_i , where $i = \{1, \dots, K\}$ is defined as follows:

$$\mathcal{S}_i(t) = \{x_i(t), y_i(t), v_i(t)\}, \quad \forall i = \{1, \dots, N\} \quad (8.1)$$

where $(x_i(t), y_i(t))$ are the coordinates of the vehicle at time t and $v_i(t)$ is the speed of i^{th} vehicle.

8.3.2 Driving Modes

As in [84], [157], we limit ourselves in an optimal deceleration scenario where three driving modes can be characterized as follows:

- Cruising: The vehicle maintains a constant speed. This mode occurs when the predicted velocity of the vehicle for lane changing is the same as the velocity of the vehicle in the current time slot, i.e.,

$$v_i(t) - \zeta \leq v_i^d(t) \leq v_i(t) + \zeta, \quad (8.2)$$

where $v_i(t)$ is the velocity of the vehicle in the current time slot, $v_i^d(t)$ is the desired velocity of the vehicle for lane changing, and ζ is a constant close to zero.

- Acceleration: The vehicle accelerates by increasing the speed with the gear not in neutral. This mode occurs when the predicted velocity of the vehicle for lane

changing is higher than the velocity of the vehicle in the current time slot, i.e.,

$$v_i^d(t) > v_i(t) + \zeta. \quad (8.3)$$

- Engine brake: The vehicle decelerates using the modern engine brake functionality with positive gear. This mode occurs when the predicted velocity of the vehicle for lane changing is lower than the velocity of the vehicle in the current time slot, i.e.,

$$v_i^d(t) < v_i(t) - \zeta. \quad (8.4)$$

8.4 Problem Formulation

This work aims to design a two-fold safety-oriented problem that considers risk and utility minimization. The risk minimization model ensures that self-driving vehicles drive safely when faced with an obstacle(s) in a road segment, and the utility minimization guarantees that there are enough resources in the network such that lane change happens safely. During emergencies, collision avoidance is difficult to provide. The TransVerse can help to ensure that the vehicles can plan emergency maneuvers to avoid collision risks and maximize safety for the vehicles affected by emergencies. While doing so, a driving mode advice could be generated to improve the velocity of the vehicle, which can compensate for the driver's reaction time for the vehicles following HRCV. The problem thus formulated is given as follows:

$$\min_{c_i, T_i^{e2e}, v_{i+1}} \mathbf{R}(v, x, y)(c_i \Gamma^c + T_i^{e2e} \Gamma^t), \quad (8.5a)$$

$$s.t. \sum_{i=1}^{V^e} c_i(t) \leq C, \quad \forall 0 \leq t \leq T, \quad (8.5b)$$

$$T_i^{e2e}(t) \leq \tau, \quad \forall 0 \leq t \leq T, \quad (8.5c)$$

$$\mathbf{R}^{ie}(v_i(t+1), x_i(t+1), y_i(t+1)) \leq \mathbf{R}^{ie}(v_i^d(t), x_i(t), y_i(t)), \quad (8.5d)$$

$$v_{min} \leq v_i^d(t) \leq v_{max}, \quad \forall 0 \leq t \leq T, \quad (8.5e)$$

where $\mathbf{R}(\cdot)$ is the risk function, c_i is the computation resources required by digital twin of i^{th} vehicle, T_i^{e2e} is the end-to-end latency required for communication and computation of the vehicular tasks, τ is the end-to-end latency threshold, Γ^c and Γ^t are the constants representing the weightage of computation resources and end-to-end latency of the vehicle. $\mathbf{R}^{ie}$ is the risk for i^{th} vehicle in the emergency lane or the lane where the accident took place, v_{min} and v_{max} is the minimum and maximum velocity limits of the vehicle. The optimization problem in (8.5a) minimizes the risk of collision and optimizes the amount of resources and end-to-end latency of the network. The constraint in (8.5b) satisfies the minimum resource requirement, i.e., the amount of computing resources required by the vehicular network. (8.5c) states that the end-to-end latency of the network must be less than the latency threshold of the network. The constraint in (8.5d) states that the risk of the vehicles in the emergency lane in the next time slot must be less than the risk of the vehicle in the previous time slot. The constraint in (8.5e) states that the velocity of the vehicle i at time slot t should be between $[v_{min} \ v_{max}]$.

8.5 Solution Methodology

It can be observed that the problem in (8.5) is a complex problem as it is dependent on the velocity of the vehicle. Thus, to ensure safe maneuvering and advise the driver about the driving mode in TransVerse-enabled connected vehicular networks, we propose Algorithm 7. The proposed algorithm takes into account the safety link quality for safe maneuvering and provides driving mode advice to the drivers of the HRCV and the vehicle in its vicinity to compensate for the driver's reaction time. The proposed algorithm utilizes the four steps, namely:

- Collision probability analysis and safe link quality: It renders ambient awareness by immediately analyzing sensory data to identify unusual behaviors such as abrupt lane changes and slowing down. The steps to swiftly determine an emergency path based on the current dynamics of the vehicles could be computed upon the recognition of emergency threats. Lane quality indicates a metric that denotes the state of lane collision risk prior to an emergency vehicle maneuver decision.
- Emergency maneuver planning: It reflects a safe lane for the vehicles to maneuver, such that the maneuver has a minimal impact on overall road safety.
- Driving mode advisory: It is safer and easier to have a driver-in-the-loop (DIL) framework before fully autonomous driving is successful [84]. We aim to provide driving mode advice and the emergency path chosen by the vehicle based on the current dynamics. This advice would focus on providing an optimal speed profile for the drivers to follow.
- latency and computation resource calculation: It reflects the calculation of latency and computation resources required by the vehicular network to plan an emergency maneuver for the vehicles in the vicinity of the emergency vehicle.

The four problems are described in detail in the following subsections. These problems are solved sequentially to evaluate the role of TransVerse in emergency scenarios for the connected vehicles.

8.5.1 Collision Risk Analysis and Safe Link Quality

To plan an emergency path for the vehicle, the first step is to analyze the quality of the safe lane that indicates the safety index of each lane during the emergency driving decision. We begin by defining the collision probability of the vehicles, followed by an emergency path selection strategy. The “collision probability” is the risk that a the

moving vehicle will collide with an obstacle ahead on the road. We denote the collision risk of vehicle i as n_i which is dependent on time-to-collision and is uniformly distributed within $T_c \in [T_{cmin}, T_{cmax}]$, where T_{cmin} is reached when a vehicle maximally accelerates toward the obstacle and T_{cmax} is reached when a vehicle minimally accelerates toward the obstacle. The risk of collision of vehicle k and l the vehicular network is computed as follows:

$$\mathbf{R}^{k,l}(v, x, y) = \begin{cases} 0, & \text{if } T_c \leq T_{cmin} \\ 1 - \frac{T_c - T_{cmin}}{T_{cmax} - T_{cmin}}, & T_{cmin} < T_c < T_{cmax} \\ 1, & \text{if } T_c \geq T_{cmax}, \end{cases} \quad (8.6)$$

where, k is the index of vehicle colliding with vehicle l and T_c is the time-to-collision between vehicle k and l .

8.5.2 Emergency Maneuvering

8.5.2.1 Path Planning

The process of emergency path planning consists of finding a path P_{em} for a vehicle $n_i \in V$ such during an entire maneuver time Δt , the collision probability P_{col} associated with the relative kinematics of adjacent vehicles shall always be low. Let the speed of the parent vehicle, n_p at time t , be denoted by $v_p(t)$. The parent vehicle is the vehicle driving in front of the child vehicle n_c , whose speed at time t is denoted by $v_c(t)$. The Euclidean distance between the cars n_p and n_c is denoted by d_{euc} . The following formula is used to determine the collision probability P_{col} for two vehicles n_p and n_c during a maneuver time Δt [80]:

$$P_{col} = \int_t^{t+\Delta t} v_i(t) dt + \epsilon_v \leq d_{euc}, \quad (8.7)$$

where the relative speed is denoted by $v_i(t) = |v_c(t) - v_p(t)|$. The error in speed measurement is denoted by $\epsilon_v \sim \mathcal{N}(0, \sigma)$, where $\sigma = 1, 2, 3, \dots, 10$ km/h [80]. The trajectory

distance $d_i(t)$ of an emergency vehicle n_i during the maneuver process is defined as follows:

$$d_i(t) = \int_t^{t+\Delta t} v_i(t) dt, \quad (8.8)$$

where $v_i(t)$ is the speed function at time t .

8.5.2.2 Emergency Maneuver

For a given sequence of vehicles, the decision-making problem to find safe maneuvers for each vehicle at the risk of colliding with neighbors is an NP-complete problem [84]. Thus, we need to find a solution to a safe lane maneuvering problem that can safely control the maneuvering of many vehicles on the road. The emergency driving decisions set S^* that maximizes the safe driving profit is defined as:

$$S^* \rightarrow \max \sum_{i=1}^N S_i, \quad (8.9)$$

where S_i is the safe lane quality of each vehicle as a safety metric in the maneuver lane.

The safe lane quality for the left lane (S^L) is calculated as:

$$S^L = \prod_{i=1}^{N_L} q_i^L, \quad (8.10)$$

where N_L is the number of hops in the left lane, $q_i^L = 1 - p_i^L$, where p_i^L is the probability of collision.

Similarly, the safe lane quality for the right lane (S^R) is calculated as:

$$S^R = \prod_{i=1}^{N_R} q_i^R, \quad (8.11)$$

where N_R is the number of hops in the right lane, $q_i^R = 1 - p_i^R$, where p_i^R is the probability of collision.

8.5.3 Desired Velocity And Driving Mode Advisory

In accordance to [85], the predicted velocity for lane changing is described by the following range policy:

$$v_i^d(t) = \begin{cases} 0, & \text{if } p_c > 0.8 \\ \frac{v_{max}}{4} \left(1 - \cos \left(\pi \left(\frac{h-h_0}{h_g-h_0} \right) \right) \right), & 0.8 \geq p_c > 0.5 \\ \frac{3v_{max}}{4} \left(1 - \cos \left(\pi \left(\frac{h-h_0}{h_g-h_0} \right) \right) \right), & 0.5 \geq p_c > 0.3 \\ v_{max}, & \text{if } 0.3 \geq p_c. \end{cases} \quad (8.12)$$

where v_{max} is the maximum possible velocity of the vehicle, h is the headway between vehicle k and l , h_{max} is the maximum headway between vehicle k and l , and h_{min} is the minimum headway between vehicle k and l .

8.5.4 Communication Link

The communication link latency when the processing is done by only one RSU, i.e., if the vehicular task is started at an RSU and is completed before the vehicle leaves the coverage area of the current RSU is calculated as follows [158]:

$$T_{ij}^r = \frac{d_i}{R_{ij}^{ul}} + \frac{d_i c_i}{f_{ij}^e} + \frac{d'_i}{R_{ij}^{dl}}, \quad (8.13)$$

where R_{ij}^{ul} and R_{ij}^{dl} are V2R uplink communication rate and downlink communication rate, respectively. f_{ij}^e is the computation resource that RSU j allocates to vehicle i .

In case the processing of vehicular tasks is handled by multiple RSUs, i.e., when the computation of vehicular tasks starts at RSU j and completes when the vehicle moves in the range of RSU k , RSU j transmits the computation result to RSU k . In such cases, the communication link between RSUs is activated, the task execution time consists of uplink latency, computation latency for the tasks, the time taken for sending the computed tasks

from RSU j to RSU k , and the downlink time required by the task. It can be expressed as [158]:

$$T_{ik}^r = \frac{d_i}{R_{ij}^{ul}} + \frac{d_i c_i}{f_{ij}^e} + \frac{v_i \Delta t d_i'}{r R_b} + \frac{d_i'}{R_{ik}^{dl}}, \quad (8.14)$$

where $\frac{d_i'}{R_b}$ is the transferring time between two adjacent RSUs, r is the coverage of each RSU, and the distance that vehicle i moving from time slot t to time slot $t + \Delta t$ is $v_i \Delta t$.

To indicate whether the task can be completed within the coverage area of the RSU j we use the $\mathbf{1}(\cdot)$. If the task is completed within the coverage area of the RSU j (i.e., $v_i T_{ij}^r < R_{RSU}$) and the task execution time is T_{ij}^r . Otherwise, the task cannot be completed within the coverage area of the RSU j (R_{RSU}). In the latter case, the task execution time is T_{ik}^r . Therefore, the task execution time when vehicle i chooses to offload the task to the RSU can be expressed as [158]:

$$T_i^{rsu} = \mathbf{1}(v_i T_{ij}^r < R_{RSU}) T_{ij}^r + (1 - \mathbf{1}(v_i T_{ij}^r < R_{RSU})) T_{ik}^r. \quad (8.15)$$

The end-to-end latency for communication, computation, and reaction latency is calculated as:

$$T_i^{e2e} = T_i^{rsu} + RT, \quad (8.16)$$

where RT is the reaction time of the users equivalent to 0.85 sec in the case of emergency situation [87].

8.5.5 Proposed Emergency Maneuver Planning

To ensure safe maneuvering and advise the driver about the driving mode in a TransVerse-enabled connected vehicular network, the planning of emergency situations must be analyzed prior. The proposed algorithm takes the help of context-aware navigation protocol design [84] to provide a safe maneuver during emergency situations. The proposed algorithm is described in detail in Algorithm 7. It takes into account the safety link quality for

safe maneuvering and provides driving mode advice to the drivers of the HCRV and the vehicle in its vicinity to compensate for the driver's reaction time. Onwards, we utilize the notation HCRV2 to indicate the vehicle following HCRV.

We begin by initializing the set of parent and child nodes according to the impact of the emergency situation. In this case, the HCRV is considered as a parent node. The vehicles following the HCRV are the child nodes. In case the parent node has any child node, the safe link quality for each lane is calculated. Depending on the safe quality index of the other lanes, lane change is suggested. Once the requirement for lane change is finalized, the risk of collision of HCRV with the vehicles in the suggested lane is calculated. The probability of collision is calculated depending on the distance between the HCRV and the vehicles in its vicinity in the suggested lane. This probability of collision between the HCRV and the neighboring vehicle in the suggested lane decides the velocity of the vehicle according to (8.12). Thereafter, the driving mode advice for the HCRV is issued. This would help the driver for the HCRV to move according to the suggested plan.

In a similar way, a lane change warning and driving mode advice is issued for the vehicle following HCRV, i.e., HCRV2, HCRV3,..., HCRV N_e . In case the vehicular network is not enabled with TransVerse, the HCRV2 would again have to go through the process of sensing the emergency situation, uplink transfer of the sensed information, processing the information for safe maneuver planning, and transfer of the processed information back to the vehicle, i.e., all the steps that were performed by the first HCRV. This process of sensing and transfer of information would consume high time. With the aid of TransVerse, the vehicles could be allocated the resources in the same slot, i.e., HCRV would follow the same processing steps as in the traditional case, where TransVerse is not deployed. However, for the HCRV2, the processing can be done much faster, as the HCRV2 could also utilize the sensed information from HCRV for emergency situation detection. Moreover, as the exact vehicle information, including current velocity and position, is available at TransVerse, thus, it is easy to calculate the position of HCRV2 and its neighboring vehicles

for the upcoming time slot. Consequently, the safe maneuver planning and driving mode advice for HCRV2 could be processed quickly. As a result of quick processing, the driver will know about the emergency situation prior, and the driver's reaction time could be compensated. However, this process would require higher computation processing at TransVerse as the safe maneuver planning and driving mode advice is processed for two vehicles simultaneously. The process required for safe maneuver planning and driving mode advice for HCRV and HCRV2 is also shown in Algorithm 7.

Algorithm 7 The Emergency Maneuvering Problem

Initialize:

- The parent node (n_p) with the HCRV vehicle, i.e., the vehicle most risky to collide with the obstacle vehicle.
 - The other nodes in the vehicular network are assigned to the child node set, n_c .
- 1: **if** $n_c \neq \phi$ **then**
 - 2: Calculate the collision probability for each node in the vehicular scenario.
 - 3: **for** each $V = 1 : N_e$ **do**
 - 4: Calculate the position of the vehicle after safe maneuver for the front vehicle in the emergency lane is designed.
 - 5: **for** each lane $l = 1 : L$ **do**
 - 6: Calculate the safe link quality (S^l)
 - 7: **if** The safe link quality of the current lane is less than any other lane, $S^c < S^l$ **then**
 - 8: Set the new lane to $\mathcal{L}^* = S^l$.
 - 9: Check for the position of vehicles in L^* .
 - 10: Check for the probability of collision of vehicle n_{em} with vehicles in $\mathbf{N}^*$.
 - 11: Decide the driving mode n_{em} according to the risk of collision. Assign it the new driving mode $\mathcal{M}^*$.
 - 12: **else**
 - 13: Set the new lane as current lane: $L^* = S^c$
 - 14: Set the current driving mode as: $M^* = \text{Brake}$
 - 15: **end if**
 - 16: **end for**
 - 17: **end for**
 - 18: **else**
 - 19: No following vehicles, and no decision needs to be taken.
 - 20: **end if**
 - 21: **Stop.**
-

8.5.6 Complexity Analysis

The vehicles in the lane where the emergency situation happens would analyze the safe link probability for all the vehicles in the neighborhood lanes, i.e., left and right lanes. Thus, the complexity of the proposed algorithm is calculated as: $\mathcal{O}(N_e(N_l + N_r))$, where N_e is the number of vehicles in the emergency lane. N_l and N_r are the number of vehicles in the left and right lanes, respectively.

8.6 Simulation Results

We utilize a simulation of urban mobility (SUMO) simulator to simulate the vehicular environment [159]. HCRV senses the emergency situation and sends the information to TransVerse. Based on the information received, a safe maneuver can be planned for multiple vehicles simultaneously. In this work, we have considered that maneuver planning for two vehicles can be processed simultaneously¹. Further, we consider a scenario where there are three lanes. The width of each lane is considered to be 3.5 m [160]. We consider a scenario where there are 5 RSUs on the road of lane segment of length 1 km and width 10.5 m. The other simulation parameters are specified in Table 8.1. In addition, we have classified the vehicular traffic scenarios into sparse, medium, and dense scenarios based on the headway distance between the vehicles. If the average headway distance between the vehicles is more than 100 m, then the scenario is classified as a sparse traffic scenario. Similarly, if the headway distance between the vehicles is between 100 m and 25 m, then the scenario is classified as a medium traffic scenario. On the other hand, if the headway distance between the vehicles is less than 25 m, then the scenario is classified as a dense traffic scenario. This classification is similar to the classification in [161], where the

¹In this work, simultaneous maneuver planning for two vehicles is considered to avoid the computation overhead on the TansVerse. As the simultaneous processing increases, more resources would be required by TransVerse with a lesser impact on latency. This would result in a lesser impact on the utility of the network.

Table 8.1: Simulation Parameters

Parameters	Definition	Values
v_i	Velocity of i^{th} vehicle	[20,140] km/hr [80]
W	Width of the road	10.5 m
L	Length of the road segment	1000 m
N_{RSU}	Number of RSUs on the road	5
$\mathbf{N}$	Vehicle density	[0.001 0.2] vehicle/m
B_u	Uplink bandwidth	10 MHz [158]
B_d	Downlink bandwidth	20 MHz [158]
f_c	computation capabilities	[10 20]GHz [158]
D_l	The input data size of each task	[1,8] MB [158]
D_u	computation result of each task	0.5 KB [158]
P_t	Transmission power	20 dBm [158]
ζ	Deviation in velocity	5m/sec
RT	Reaction Time	0.85 sec [87]

authors have classified the traffic scenarios based on the distance between the interfering vehicles.

Fig. 8.2 shows the probability of HCRV for each driving mode. It can also be observed that the probability of braking is higher than that of the other two modes. This is because there is a high probability that HCRV tends to stop or decelerate when it observes the obstacle. In addition, it can be observed that the probability of applying the brake or acceleration is higher than that of cruising. It is because in an emergency situation, there is a high probability that the vehicle will get a clear or busy road. In the case of a clear road, the vehicle will accelerate during lane change; otherwise, the vehicle will stop and wait for the road to be clear. The probability of cruising is lower than the probability of the other two modes. This can also be observed from Fig. 8.2, where the probability of braking and acceleration is 32.14% and 25.925% higher than the cruising mode, respectively. Further, the effect of T_{cmax} on the driving probability can also be observed from Fig. 8.2. It can be observed that as T_{cmax} increases, i.e., the vehicles minimally accelerate towards the obstacle, the probability of HCRV being in higher speed of driving increases, i.e., probability of acceleration increases. Thus, with an increase in T_{cmax} from 5sec to 10sec, the probability of acceleration increases by 3.03%, and the

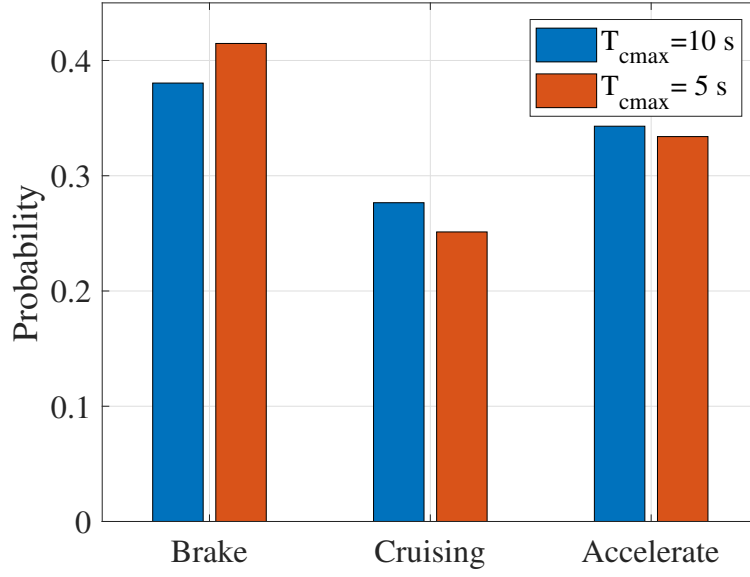


Figure 8.2: Probability of Driving mode

probability of braking decreases by 11.90%.

The suggested velocity for lane changing of HCRV with respect to the vehicle density is presented in Fig. 8.3. It can be observed that as the vehicle density increases, the velocity of the HCRV decreases. For $T_{cmax} = 5$ sec, the velocity of HCRV decreases from 85km/hr to 67km/hr as the vehicle density of each lane increases from 0.01 to 0.2 vehicles/m. In addition, it can also be observed that as T_{cmax} increases, the suggested velocity for lane changing of the HCRV increases. For vehicle density of 0.16 vehicles/m, the velocity of the HCRV increases by 7.01% as T_{cmax} increases from 5 sec to 10 sec. In addition, it can be observed that the velocity of the vehicles decreases from 85 km/hr to 61 km/hr as the vehicle density increases by 0.068 vehicle/m, whereas for dense traffic scenarios, the velocity of the vehicles decreases by 3 km/hr. This is because, in the sparse traffic scenario, the vehicles have enough space to change the velocity; however, in the case of the dense traffic scenario, there is no significant change in the velocity of vehicles.

Further, in Fig. 8.4, the safe link quality for HCRV is presented. It can be observed that as the vehicle density increases, the safe link quality decreases. This is because as the

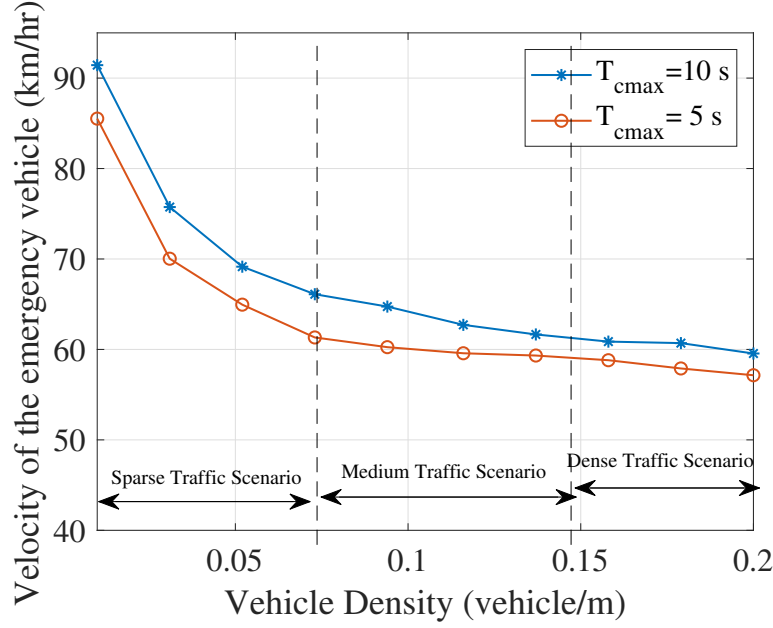


Figure 8.3: Suggested velocity for HRCV

density of vehicles increases, the risk of collision increases, and the probability of collision for the vehicles increases. It can be observed that with TransVerse scenario, the safe link quality decreases by 0.602 and 0.006 for sparse and medium traffic scenarios, respectively for T_{cmax} . Further, it can also be observed from Fig. 8.3 that with the increase T_{cmax} , the velocity of the vehicle during lane changing increases. This increases the collision risk of the vehicles, which results in a decrease in safe link quality.

The risk of collision of HCRV2 with respect to vehicle density is presented in Fig. 8.5. It can be observed that the risk increases with the increase in vehicle density. This is because as the number of vehicles increases on the road, the probability of collision increases. Specifically, the risk of collision for HCRV2 increases by 5% for sparse traffic scenario for scenario with TransVerse. Whereas it increases by 2% for medium and sparse traffic scenarios. Further, it can also be observed that with the use of TransVerse, a safe maneuver can be designed for HCRV2. Thus, the probability of collision for HCRV2 decreases by 24.16% for 0.16 vehicle density.

Fig. 8.6 presents the variation in the velocity of HCRV2 with respect to vehicle den-

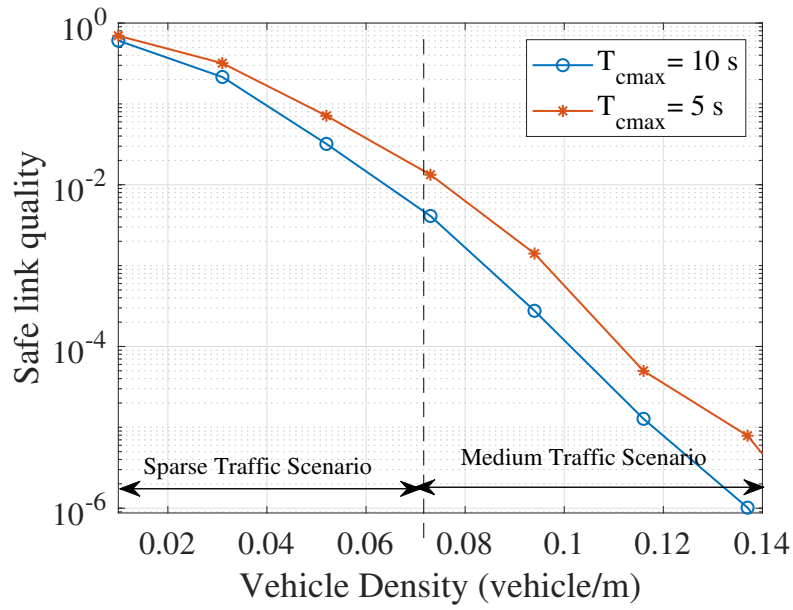


Figure 8.4: Safe link quality for HRCV

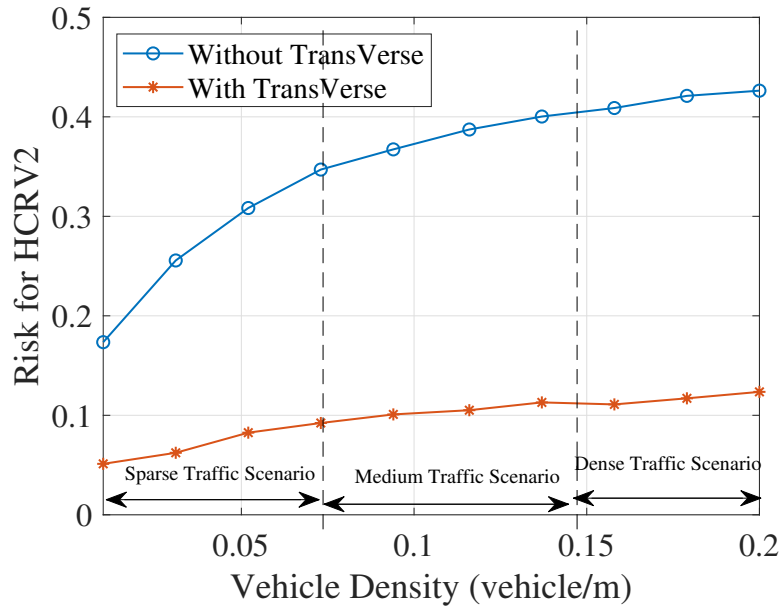


Figure 8.5: Risk for HRCV2

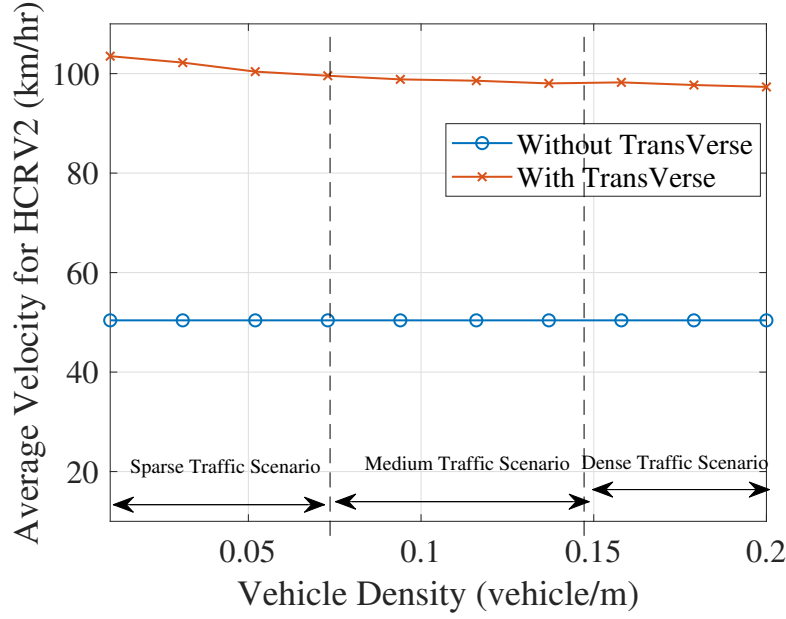


Figure 8.6: Suggested Velocity for HCRV2

sity. It can be observed that without TransVerse, the velocity of the vehicle remains the same as that of the average velocity from the previous time slots and, therefore, remains constant; however, with the utilization of TransVerse, the velocity of the vehicle increases from the previous time slot. This is because of prior safe maneuver planning. Due to safe maneuvering, the vehicles can move on the road without any need to worry about emergency situations; thus, the vehicles' velocity increases. Specifically, with the utilization of TransVerse, the average velocity of HCRV2 decreases by 5 km/hr for sparse vehicular traffic scenario as compared to without TransVerse scenario. Similarly, for medium and dense vehicular traffic scenarios, the average velocity of the vehicle decreases by 3 km/hr and 2 km/hr, respectively. Further, it can also be observed that the velocity of the vehicles decreases as the vehicle density increases. This is due to the fact that as the vehicle density increases, there will be more vehicles on the road, which would decrease the speed of HCRV2.

Fig. 8.7 presents the time-to-collision for the scenarios with and without TransVerse of HCRV2 with respect to vehicle density. It could be observed that without TransVerse,

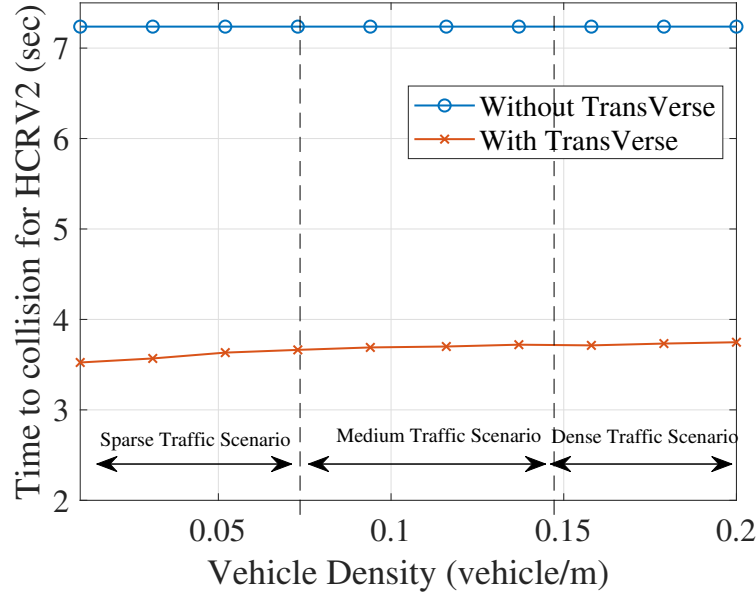


Figure 8.7: Time-to-collision for HCRV2

time-to-collision remains constant with vehicle density as it depends on the distance between the vehicles and the velocity of the vehicles. As can be observed from Fig. 8.6, the velocity of the HCRV is constant with respect to the vehicle density. Thus, the time-to-collision also remains constant with respect to the vehicle density. Further, it can also be observed that in with TransVerse scenario, the vehicle time-to-collision decreases compared to the without TransVerse scenario. This is due to the fact that with safe maneuver planning, the probability of collision would reduce in the vehicular network, which increases the time-to-collision in the vehicular network.

The network's end-to-end communication and computation latency is presented in Fig. 8.8. The end-to-end latency taken by the network is an aggregation of communication (uplink and downlink), computation, and reaction latency of the vehicular network. It can be observed that with the aid of TransVerse, a safe maneuver can be planned for the network, which reduces the uplink latency required by the network in every time slot. Thus, the information need not be transferred at each time slot for the vehicles following HRCV. This reduces the end-to-end computation and communication latency for

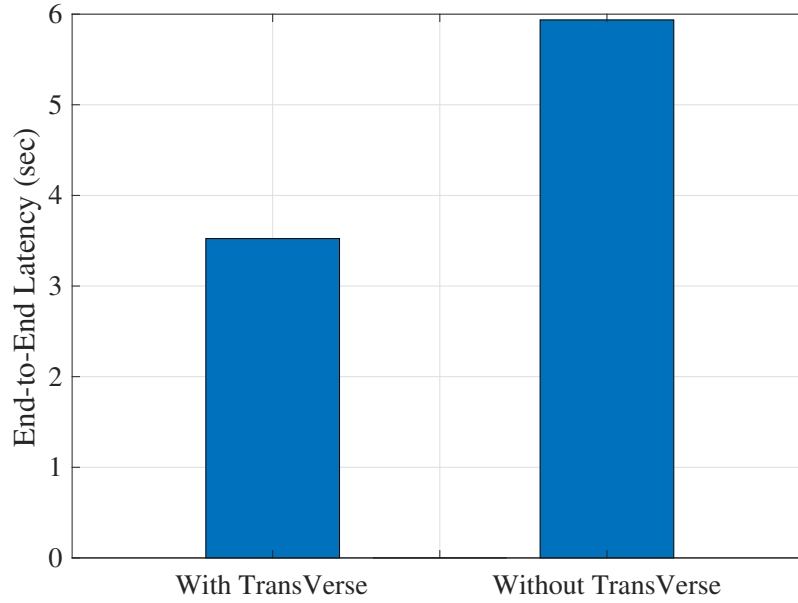


Figure 8.8: End-to-end communication, computation, and reaction latency for HCRV2

the vehicles following HRCV. From Fig. 8.8, it can be observed that with the utilization of TransVerse, the end-to-end computation and communication latency of the vehicular network reduces by 40%. Further, it can be observed that with the utilization of TransVerse, the end-to-end latency for HCRV2 is reduced by 1.4 sec; however, according to [87], the reaction time of the driver is 0.85 sec. Thus, with the utilization of TransVerse, the reaction time of the driver can be compensated.

Further, the computation resources required by the vehicular network are shown in Fig. 8.9. It is known that TransVerse would require higher computational resources, i.e., with the utilization of TransVerse, information for multiple vehicular users would be processed simultaneously by the digital twin. This would require more computation cycles at the digital twin network. This is also shown in Fig. 8.9, where with the utilization of TransVerse, there is an increase in 50% computational resources. These resources are computed considering the amount of computation required to process the information for multiple vehicles simultaneously. In this work, we have considered that the computation resources are computed for two vehicles simultaneously. As the number of vehicles for

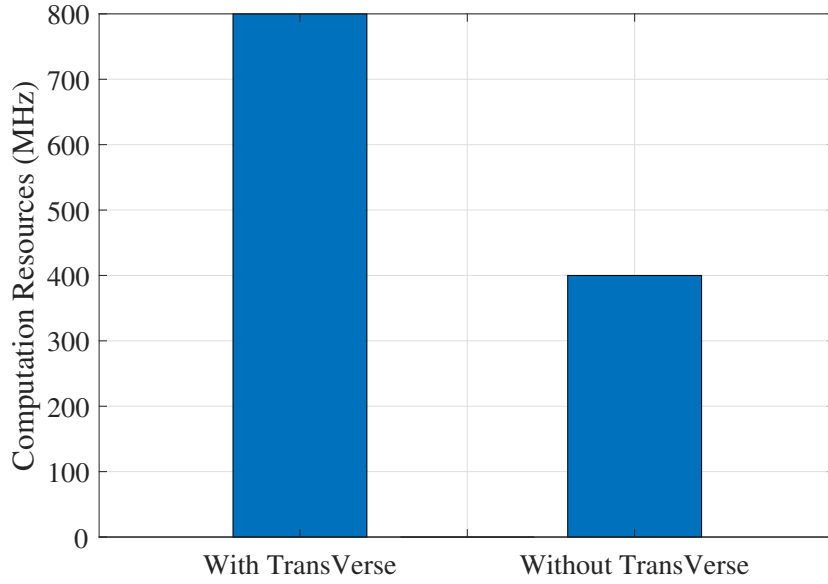


Figure 8.9: Computation resources required for HCRV2

which simultaneous computation is required increases, the computation resources required by the vehicular network increase.

8.7 Conclusions

This chapter considers a pre-emptive emergency situation and designs a safe-driving maneuver design problem for TransVerse enabled connected vehicular network. The emergency maneuver is defined to compensate for driver reaction delay. A connected vehicular network is designed that balance the risks and utility of the network. We designed a safe maneuvering mechanism for vehicles in the emergency zone. This safety maneuver is proposed to design a safe lane-changing maneuvering based on a safe link quality index. Further, based on the current position of the vehicles and the proposed safe maneuver planning, we proposed a driver mode advisory to the drivers to provide a speed profile and real-time high-level driving mode advice such as acceleration, cruise, and engine brake. We evaluate the performance of the proposed safe-maneuver planning for CRV, i.e., the

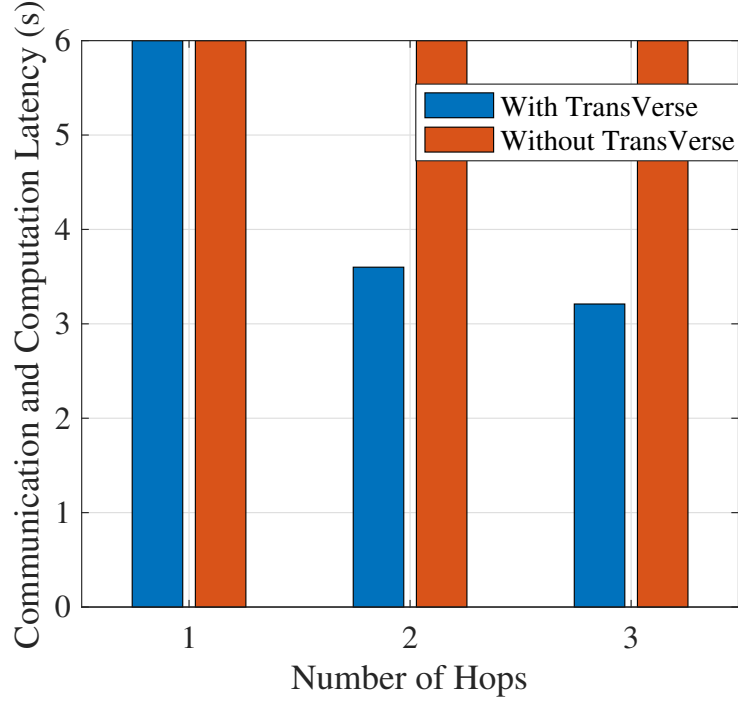


Figure 8.10: Variation of end-to-end communication, computation, and reaction latency with respect to the number of nodes.

vehicle following the emergency vehicle in terms of collision probability, the velocity of the vehicles, driving mode, end-to-end lane changing delay, etc. It can be observed that with the use of the proposed scheme, there is no effect on the performance of the vehicle in the vicinity of the emergency vehicle. However, for the 2nd following vehicle (HCRV2), the probability of collision decreases by 34.78%, and the velocity of the vehicle increases by 61.70%. Moreover, it can be observed that with the utilization of TransVerse, the end-to-end delay for HCRV reduces by 40%. Further, it can be observed that with the utilization of TransVerse, the end-to-end delay for HCRV2 is reduced by 1.4 sec; however, the reaction time of the driver is 0.85 sec. Thus, with the utilization of TransVerse, the reaction time of the driver can be compensated. However, the utilization of TransVerse increases the computation resources required by the vehicle by 50%. Thus, a trade-off between end-to-end delay and computation resources required by the network is observed with and without the TransVerse scenario. ’

Chapter 9

Conclusions

This chapter concludes the work presented above, followed by future research directions. Firstly, in order to mitigate the conventional limitations of grid-power supply, an off-grid FiWi network is considered, where the components of the network such as ONUs and IEEE 802.11 APs are powered using renewable sources of energy such as PV panels and wind turbines along with batteries. Depending on the availability of renewable power at different locations, the energy resources available to power ONU-AP may vary. We proposed the algorithms to allocate the minimum number of batteries and PV panels so that a 24-hour power supply can be provided to ONU-APs. The results demonstrate that the resource requirement also varies due to the difference in available solar power profiles at different locations. Further, we proposed a joint energy resource optimization framework to allocate energy resources to power ONU-AP. A two-step iterative algorithm is employed to calculate the energy resources required by ONU-AP. Moreover, in order to validate the accuracy of the algorithm, an analytical framework is derived. The good agreement between the results of the analytical and iterative approach justifies the accuracy of the proposed framework. Furthermore, a socioeconomic analysis is presented to analyze the impact of energy resource allocation on CO₂ emissions and the cost of the system. Moreover, we compare the performance of our proposed approach, *MERA*, with that of non-ML-based approaches. The results showed that using *MERA*, there is a reduction in energy resource allocation, cost, CO₂ emissions, as well as outage compared to *Max* energy resource allocation, which is the best case scenario. However, in comparison to *Max* resource allocation, there is a reduction of battery lifetime by 10%. Thus, a

trade-off between energy resource allocation and lifetime has been shown in this work.

In addition to the above, we classified the network data traffic based on KPI. We use the deficit DBA algorithm to enhance the throughput of the FiWi network. Specifically, we are able to achieve a throughput of 100 Mbps per user for an integrated network. The use of high-end wireless standards such as IEEE 802.11ac based WLAN helps in achieving the QoS parameters within the tolerable range of ITU-T standards. The results demonstrate that for voice, we are able to achieve the PLR within a tolerable range of ITU standards for a network load of 80%, and for video, the PLR is maintained within a tolerable range for a network load up to 60%. Moreover, the results demonstrate that for a fully loaded network, we are able to achieve an aggregate throughput of 62.5% of the XG-PON upstream capacity.

Furthermore, the above work was extended to vehicular network traffic scenarios where we proposed an ML-based T-CONT priority assignment wavelength allocation algorithm to meet the stringent requirements of 6G vehicular traffic. In order to facilitate the above, a mapping between the various kinds of vehicular data traffic and their 6G KPIs, namely throughput, latency, and reliability, is studied. Thereafter, we classified the V2I traffic among four classes based on their KPI requirements. Each class of traffic is assigned to a T-CONT for wavelength allocation at each ONU-RSU. By exploiting vehicular traffic predictions through ML, a framework is proposed to allocate the wavelength to the ONU-RSUs. The efficiency of the proposed ML-based T-CONT priority assignment wavelength allocation algorithm is compared with the other approaches, namely equal T-CONT allocation and random wavelength allocation algorithm in terms of e2e latency, throughput, and reliability. Further, we proposed an energy and latency-aware V2V data offloading scheme for FiWi-based vehicular networks. Specifically, we utilized a NG-PON2 based back-end network with vehicular network at the front-end. To do so, we classified vehicular traffic into four categories according to their KPIs and proposed a V2V data offloading scheme for high-priority vehicular data. In order to ensure that the network is

energy efficient and has improved QoS, we propose a reinforcement learning based DDQN scheme for choosing the cluster-head for V2V communication. The performance of the proposed algorithm is compared with the non-RL-based approach, such as random and max-queue-based cluster-head selection.

Moreover, we designed a safe maneuvering mechanism for vehicles in the emergency zone considering a preemptive emergency scenario. This safety maneuver is proposed to design a safe lane-changing maneuvering based on safe link quality index. Further, based on the current position of the vehicles and the proposed safe maneuver planning, we proposed a driver mode advisory to the drivers to provide a speed profile and real-time high-level driving mode advice such as acceleration, cruise, and engine brake. We evaluate the performance of the proposed safe-maneuver planning for CRV, i.e., the vehicle following the emergency vehicle in terms of collision probability, the velocity of the vehicles, driving mode, end-to-end lane changing latency, etc. It can be observed that with the use of the proposed scheme, there is no effect on the performance of the vehicle in the vicinity of the emergency vehicle. However, for the HCRV2, the probability of collision decreases by 34.78%, and the velocity of the vehicle increases by 61.70%. Moreover, it can be observed that with the utilization of TransVerse, the end-to-end latency for HCRV reduces by 40%. Further, it can be observed that with the utilization of TransVerse, the end-to-end latency for HCRV2 is reduced by 1.4 sec; however, the reaction time of the driver is 0.85 sec. Thus, with the utilization of TransVerse, the reaction time of the driver can be compensated.

Thus, the frameworks proposed in this dissertation can be efficiently utilized to provide QoS guarantees by efficient resource allocation not only in the static FiWi network scenarios but also for the mobile vehicular networks. This will be helpful for a communication engineer to design a sustainable system that exploits new technologies, such as DT-enabled Metaverse, to guarantee the required QoS to the end users.

9.1 Future Scope

The thesis lays the groundwork for several prospective extensions. The subsequent section outlines several potential avenues for future research directions.

9.1.1 Digital Twin Assisted RIS Enabled Green Connected Vehicular Network

Recently, the research community has been focusing on emerging technologies such as DT, blockchain, XR, etc. However, these technologies have not yet been explored much for reconfigurable intelligent surface (RIS) enabled connected vehicular networks. The integration of a DT with a connected vehicular network would enhance the bandwidth allocation to improve the QoS to the users. The DT network would enable the real-time tracking of the position of vehicles on the road, which will eliminate the need for periodic data transfer to the central controller. Fig. 9.1 presents a DT-assisted RIS-enabled connected vehicular network. The DT facilitates highly efficient synchronization, monitoring, and data sharing among various real-world infrastructures (using traffic light signals), vehicles (utilizing head and taillight transmission), pedestrians, and more. It significantly improves resource allocation efficiency and optimizes system parameters. The feedback from DT will enable the RIS to adjust its phase automatically based on the information of the vehicular network, which will enhance the QoS of the vehicular users along with the consideration of human-related issues in the network. More importantly, a green vehicular network would be established to provide a sustainable future.

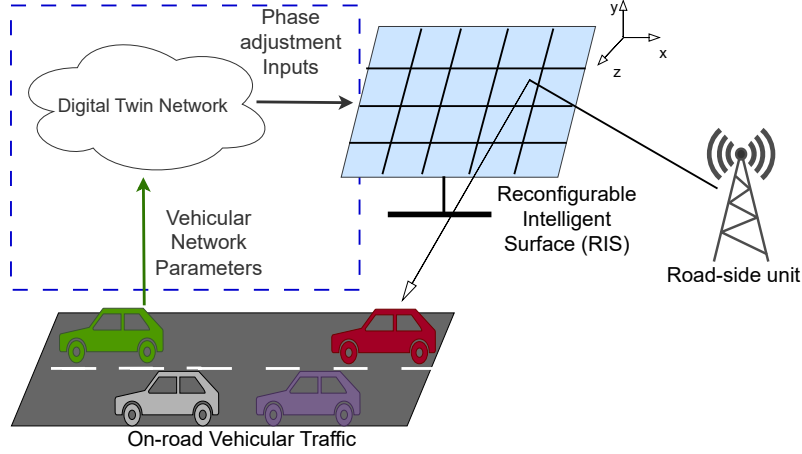


Figure 9.1: Digital Twin Assisted RIS Enabled Green Connected Vehicular Network

9.1.2 Priority Aware DT-Enabled Hybrid RF/VLC-Enabled Vehicular Network

The integration of DT with optical networks would enhance the bandwidth allocation to improve the QoS to the users. One such work could be priority aware DT-enabled hybrid RF/VLC-enabled vehicular network. The DT network can synchronize and learn real-world data traffic information based on the current network statistics. As shown in Fig. 9.2, depending on the services required by the data traffic, a priority could be assigned to the data. The high-priority data (the data that require immediate attention, such as accidents or emergency braking) could be sent through a vehicular visible light communication link, and low-priority data could be offloaded to RSU for computation. This would enable the network to prioritize the vehicular network traffic and assign resources to enhance the QoS of the vehicular users.

9.1.3 Others:

1. ISAC-assisted RIS-enabled connected vehicular network: As intelligent transportation systems continue to advance, there is an increasing focus on integrated sensing

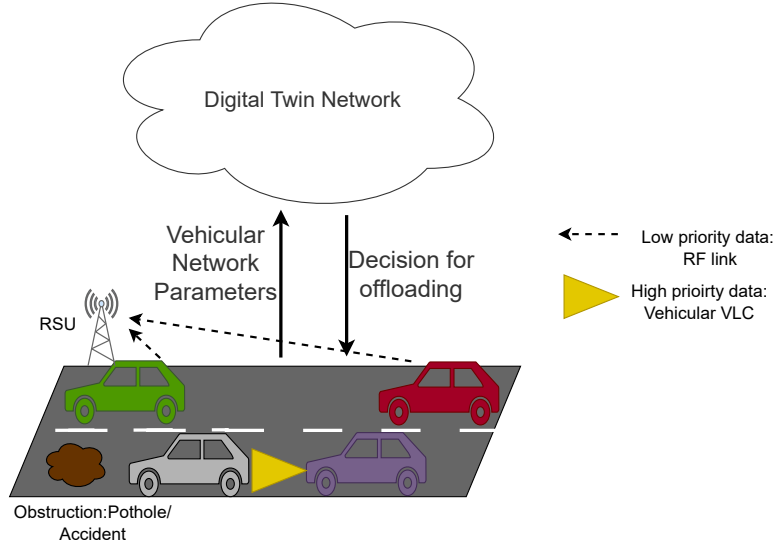


Figure 9.2: Priority aware DT-enabled hybrid RF/VLC-enabled vehicular network

and communication (ISAC) systems. RIS can be utilized to gather information about a vehicle's direction of arrival. This information can thereafter be utilized to assist vehicular communication.

2. Smart traffic cycle control framework using DT: Traffic congestion at intersections is a common issue in urban areas, causing delays, inefficiencies, and increased waiting time. This provides an opportunity to optimize traffic light control, which is crucial for improving traffic flow and reducing congestion.
3. DT enabled time ahead resource allocation for connected vehicular network: To address the key challenge of computation and spectrum resource allocation for vehicular networks, we can develop a DT-enabled time-ahead resource allocation algorithm to QoS by intelligently offloading vehicular data traffic.

Publications

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3. Akshita Gupta, Vivek Ashok Bohara, Anand Srivastava, “Digital Twin for Connected Vehicular Network: A Road Towards Sustainable Future,” accepted to IEEE Systems, Man, and Cybernetics Magazine, Sept. 2024.
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