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Improving Energy Sustainability in Electrical Vehicle Energy Networks and Internet of Things

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Improving Energy Sustainability in Electrical Vehicle Energy Networks and Internet of Things

Abdurrahman ARIKAN, Ph.D.

University of Connecticut, 2015

ABSTRACT

Energy sustainability is a pressing issue facing the modern society. The twin pillars of sustainable energy are renewable energy and energy efficiency. In this dissertation, we propose novel architectures and approaches to improve energy sustainability in two application domains: transportation and the Internet of Things. Transportation is one of the major sources of energy consumption and environmental pollution. Plug-in hybrid electric vehicles (PHEVs) present many opportunities in improving energy efficiency and reducing greenhouse gas emissions. In addition, with batteries and built-in mobility, PHEVs can form a mobile and distributed energy network, where energy can be conveniently transported from place to place. In the first part of this dissertation, we investigate how to optimally distribute renewable energy in a distributed PHEV energy network under two system architectures. The first architecture assumes that each charge station is equipped with energy storage to serve as an energy exchange point. Some PHEVs can be charged by renewable energy sources and discharge energy at a charge station. Other PHEVs passing by the charge station can withdraw energy from the charge station, and therefore indirectly use the

energy from the renewable energy sources. The second architecture assumes that the charge stations do not have energy storage. Instead, they are connected using underground cables to a central energy storage (CES), which has a limited capacity and is charged by renewable energy sources. PHEVs can withdraw/deposit energy from/to the CES (and thus indirectly use renewable energy) through the charge stations. We formulate and solve the optimal renewable energy transfer problem under each of the two system architectures. The two optimization problems share the same objective function to maximize the total amount of renewable energy used by the PHEVs but are subject to different constraints derived from the system architectures. Simulation results using the data set from the Manhattan city bus system demonstrate that our approaches significantly outperform baseline schemes and provide effective ways to share renewable energy in PHEV energy network and thus improve energy sustainability.

We further study the energy sustainability problem in a broader application domain - Internet of Things (IoT). IoT is the network of things that enables devices to exchange data with manufacturers, operators or other devices. It is expected that there will be nearly 26 billion devices on the IoT by 2020. Energy efficiency is a critical issue in the IoT. In the second part of the dissertation, we investigate energy-efficient packet transmission in the IoT. Specifically, we consider a mobile network with group-based encountering. The optimization goal is to minimize the delay for transmitting a set of packets from a source to a destination while limiting the energy consumption. The challenge lies in how to schedule packet transmission among a group of nodes that meet each other so that information carried by the different nodes can be exchanged effectively. We first assume that node encountering is known beforehand, and develop a max-flow based algorithm that obtains the optimal solu-

tion. While the assumption is clearly unrealistic, the optimal solution is useful to quantify the effectiveness of different heuristic algorithms. Specifically, we propose two network coding based heuristic algorithms. One algorithm uses full signaling where nodes exchange their coefficient matrix with each other while the other incurs much less signaling overhead in that nodes only exchange rank information when meeting each other. Both algorithms use a token-based technique to limit the total number of transmissions, and only incur signaling at the beginning of a group meeting. Simulation results demonstrate that both algorithms achieve delays close to the minimum latency for moderate number of tokens. They present different tradeoffs in the number of transmissions and the signaling overhead.

Improving Energy Sustainability in Electrical Vehicle Energy Networks and Internet of Things

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APPROVAL PAGE

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”Gravity explains the motions of the planets, but it cannot explain who set the planets in motion. God governs all things and knows all that is or can be done”

Sir Isaac Newton

It has been a long journey.

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Chapter 1

Introduction

1.1 Energy in Transportation

19th century has witnessed incredible achievements by human beings, especially in transportation industry. Innovative technologies to build up powerful trains, aircrafts and ships have enabled human beings to travel around the world for a lower cost and with less time.

In the industrialization age, with the capability of mass production, many countries have started to produce different transportation vehicles. It boosted the global economy by providing more convenient and reliable logistic services. Further, in metropolitan areas, municipalities started to offer public transportation services to reduce travel costs for public interests. Even though we have advanced in technology to reduce time cost and expenses to move around, the energy sources that are used to run transportation vehicles remained the same: fossil fuels. Most of the vehicles we use today still rely on them to propel their conventional combustion engines. Fossil

fuels are primitive and environmentally harmful petroleum products [8]. One of the reasons to use fossil fuels is that they are mature commodity and convenient [22].

Combustion engines use fossil fuels in transportation because they can easily convert chemical energy coming from liquid fuel into mechanical energy, which can be stored in a vehicle tank. Another reason for using petroleum is that distribution network of processed fossil fuels product covers most cities in any country, even though prices may vary due to the demand of gasoline. It can be transported by ships or pipelines all over the world. Petroleum is hidden in the deep locations of the earth. Discovery and extraction processes take time and can be very expensive. Once it is obtained, many processes are necessary to convert it to usable forms [22].

Besides expensive operations, using fuel products also causes ecological changes. In order to convert their stored potential energy to other energy forms, they have to be burnt. Since fossil fuels are geologic deposits of organic materials, their residue is dangerous for the environment and causes climate changes [9]. Conventional vehicles (with combustion engine types) produce almost half of the air pollution by gas emission, according to US Environmental Protection Agency [37] and it has already started to threaten large cities [24]. At the early stage, the gas emissions of mass transportation was not questioned regarding health issues and energy consumption. It has been realized later that it has many side effects including pollution and economical dependency [24]. Traditional vehicles has gas emissions. The traditional combustion engines emit many pollutants to the air such as nitrogen oxides (NO_x) and carbon monoxide (CO). According to American Public Transportation Association, the total CO_2 emission of mass transportation vehicles is the biggest share in total emission in public vehicles [24].

The main problem of fossil fuels is sustainability. It is not renewable which means

it cannot be reproduced [9]. US Energy Information Administration (EIA) indicates that fossil fuels meet around 82% of U.S. energy demand and transportation shares almost 30% of the oil demand [7].

Opposite to fossil fuels, some energy sources are called green due to their zero gas emissions. Green energy is not only environmental friendly, but also cheaper and sustainable since it can be regenerated from renewable resources [18]. One of the benefits to have green energy is that it is easily convertible to electricity which is the most used energy form in the world [7].

1.2 Electrical Energy in Transportation

Since last century, electricity has become prominent in energy industry. Its wide adoption, easy transmission and affordable price have made it an inevitable need for most of the world. Today, more than 90% of the energy sources in the world is used to produce electricity [6]. Electricity is not found in the world naturally so it is not primary, but called secondary energy source. It has to be generated by using primary resources. Although we have many ways to generate electricity, mostly non-renewable energy sources are used. According to USA Energy Information Administration [1], more than 85% of the electricity comes from non-renewable energy sources.

Electricity can be obtained from naturally replenished reserves that are available in the environment such as wind, sunlight, rain, waves, *etc.* Renewable energy generation is not easy and may have other difficulties [59], but the sources are sustainable so renewable energy can supply significant amount of demand. According to Renewable 2015 Global Status Report [45], the most reliable renewable source to generate

electricity are sunlight and wind. Not only they are reliable, but also installable to remote and urban locations [45].

Electrical energy has many advantages to cope with the problems caused by conventional engine vehicles in transportation. Recent research has shown that electrical energy can be used in vehicles. Using electricity in vehicles is feasible and reliable [62]. Electrical vehicles can reduce gas emissions. They can even make zero emissions if the vehicle is equipped with fully electrical engines [62].

Instead of using traditional approaches, Electrical Vehicle (EV) technologies can be used in vehicles in big cities to reduce both gas emission and operation expenses. Specifically, public transportation powered with plugged in hybrid electrical vehicles (PHEV) can be more cost-effective and environmental friendly than using conventional vehicles [67]. Using PHEV in public transportation has already been adopted in many large cities [15]. A detailed feasibility study of utilizing electrical energy in public transportation can be found in [81].

Compared to conventional vehicles, electric PHEVs present many opportunities in improving energy efficiency and reducing greenhouse gas emissions, and hence have the potential to significantly reduce the environmental pollution caused by transportation. In addition, equipped with batteries and due to their built-in mobility, coordinated PHEVs can form a mobile and distributed energy storage system. Within the system, energy can be conveniently transported from place to place.

In this dissertation, we first investigate the optimal renewable energy transfer problem in a bus system. Specifically, the goal is to determine how much energy a bus should deposit or withdraw at a charge station so that the total amount of renewable energy used by the bus system is maximized. We formulate and solve the optimization problem using linear programming. Later on centralized version

of the problem is studied. Simulation results using the Manhattan city bus system demonstrate that both distributed and central approaches outperform a designed baseline schemes and provide an effective way for distributing renewable energy in bus systems.

1.3 The Internet of Things

According to International Telecommunication Union, Internet of Things (IoT) is “*a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies*” [43]. The basic unit of IoT is a device with communication capability with other devices, and can participate in sensing and control tasks. The technology behind IoT makes sensing and control mechanisms possible. It provides the communication fabric interconnecting the physical world and cyber systems, thus can find many application areas, such as economy, environment and health [84]. IoT is a natural extension of the existing Internet infrastructure. By connecting physical devices to the Internet, each device in IoT can be accessed through the current Internet infrastructure. In IoT, every physical object is a potential IoT device. In addition, manufactures are consistently producing a large number of small devices for IoT in business. So the number of IoT devices around the world is increasing every day. According to Cisco [26], there will be more than 40 billion IoT devices in near future.

Connecting physical devices to the Internet can extend the technological limits. Light can be adjusted according to the comfort level of the occupant [20], one can

find a parking spot in a busy town [41], utility expenses of a house can be reduced by using smart IoT devices [90] or we even deploy IoT devices on roads and high ways to avoid traffic congestion [102]. IoT application domains can cover a variety of areas from health-care to agriculture [33, 58, 69, 78, 87].

IoT can grant “*things*” the remote programmability to sense environment and take actions. It makes the physical world and cyber world closely coupled [74]. One of the key challenges in IoT is how to connect physical devices to the Internet. In [51], the implementation uses many small IoT enabled sticker beacon hardware which has Bluetooth and iBeacon technology with cloud computing services. Sticker-like beacons can broadcast a variety of information about the physical objects they stick to including locations, temperatures, identity, ownership. Nowadays, almost every mobile phone has many built-in sensors. They are also IoT devices and a ubiquitous network can be formed if there is enough number of smart phones around.

The main contribution of IoT to the world is the remote control. Since objects can be anywhere, IoT can make accessing their status possible by querying responsible IoT device through the Internet. Furthermore, more intelligent IoT device can decide the best action for human beings by sensing, learning and adjusting the surrounding environment [13]. Last decade has witnessed many technological innovations to enable IoT devices to control home appliances. A programmable, self-learning, smart IoT thermostat can drive the home temperature according to the user preference [42]. Similarly, every appliance at home can be converted to a IoT device by using the technology explained in [51]. Efficient management of their energy usage can be provided as a service by IoT technologies [50].

1.4 Energy usage in Internet of Things

IoT devices are in general with a small form factor and very limited batteries for the sake of mobility. They have been designed to create autonomous networks to collect data and transport them to a designated destination via the Internet when it is possible [52]. In order to do that a network is desired to provide stable and reliable communication. Most IoT devices are equipped with communication modules. To interconnect IoT devices and prolong the network lifetime, energy consumption must be carefully managed [38]. Among the many key functions of the IoT device, the packet transmission and reception consumes a large portion of the battery power [29]. Many communication protocols have been developed to achieve energy-aware wireless communication [17, 75, 101]. IoT devices are battery limited equipment and require a light-weight design for communication protocols in order to maintain their functionality to connect to the Internet. Recently Internet Engineering Task Force adopts a new protocol called *6LoWPAN* [30]. It supports much more devices by assigning each IoT device an IPv6 device. Although advanced header compression techniques have been applied in 6LoWPAN, energy-efficient network layer routing and data link layer scheduling approaches are still desired to further reduce the network energy consumption [49]. Many methods have been developed to improve energy efficiency in IoT devices from both hardware and software aspects [47, 71, 83].

To achieve energy efficiency in IoT is the key challenge. Along with employing more advanced hardware and adding more software functions, IoT devices are expected to be more energy-hungry. In most applications, energy usage of IoT devices is dominated by the sensing and communication modules. In addition, due to the nature of mobility, IoT networks are dynamic [47]. They might be offline during a

non-contact time period in order to save energy.

In many designs, IoT devices are mobile and do not require to connect to the Internet all time, so the network formed by IoT devices needs to be delay tolerant for both reliable communication and efficient energy management. Designing disruptive tolerated communication algorithms in application layer for IoT devices can improve energy efficiency. Specifically, controlling their neighbor search and communication paths will significantly reduce the power consumption [14].

Recently, to tackle delay and disruption issues in wireless networks, network coding techniques have been introduced [54]. Network coding [11] can facilitate distributed and localized routing strategies, where nodes make independent decisions relying on knowledge about the local neighborhood [31]. These strategies are particularly attractive for delay tolerant networks (DTNs) due to rapidly changing topology, intermittent connectivity and limited bandwidth in the network.

In this dissertation we develop two different coding schemes for IoT devices by using network coding technique [94]. First we introduce a matrix-based scheme which considers full signaling based on the coefficient matrices of the coded packets buffered at the nodes in order to take advantage of reliable connection. In this method, all the nodes exchange coefficient matrix of their encoded data. Second we further propose rank-based algorithm which provides less data exchange simply based on the ranks of the coefficient matrices and it requires only exchanging rank information of that coded data matrix. We observe that if the communication time can be reduced, the total energy consumption will be decreased. To make matrix-based and rank-based schemes to be energy-efficient, we also use tokens to restrict number of transmission that they do while nodes (IoT devices) are within the communication range. Simulation results show that there is a tradeoff between two schemes. Detailed study can be seen in

Chapter 3.

1.5 Main Contributions

We propose novel architectures and approaches to improve energy sustainability in two application domains: transportation and the Internet of Things. Transportation is one of the major sources of energy consumption and environmental pollution. Electrical vehicle technology can solve mentioned problems. Especially, plug-in hybrid electric vehicles (PHEVs) present many opportunities in improving energy efficiency and reducing greenhouse gas emissions. PHEVs do not emit any gas during daily commute when they have electricity. In the absence of electricity, PHEVs switch back to gasoline to continue their commute. In addition, with batteries and built-in mobility, PHEVs can form a mobile and distributed energy network, where energy can be conveniently transported from place to place which is look like a communication network except using energy packets instead of data.

In the first part of this dissertation, we investigate how to optimally distribute renewable energy in a distributed PHEV energy network under two system architectures. The first architecture assumes that each charge station is equipped with energy storage to serve as an energy exchange point. Some PHEVs can be charged by renewable energy sources and discharge energy at a charge station. Other PHEVs passing by the charge station can withdraw energy from the charge station, and therefore indirectly use the energy from the renewable energy sources. This eliminates expensive extra PHEV charging facilities at the beginning.

The second architecture assumes that the charge stations do not have energy stor-

age. Instead, they are connected using underground cables to a central energy storage (CES), which has a limited capacity and is charged by renewable energy sources. PHEVs can withdraw/deposit energy from/to the CES (and thus indirectly use renewable energy) through the charge stations. For the second part, energy lost while transmission is considered. We formulate and solve the optimal renewable energy transfer problem under each of the two system architectures. The two optimization problems share the same objective function to maximize the total amount of renewable energy used by the PHEVs but are subject to different constraints derived from the system architectures. Simulation results using the data set from the Manhattan city bus system demonstrate that our approaches significantly outperform baseline schemes and provide effective ways to share renewable energy in PHEV energy network and thus improve energy sustainability.

In the second part of the dissertation, we investigate energy efficient packet transmission in the IoT. Specifically, we consider a mobile network with group-based encountering. The optimization goal is to minimize the delay for transmitting a set of packets from a source to a destination while limiting the energy consumption.

The challenge lies in how to schedule packet transmission among a group of nodes that meet each other so that information carried by the different nodes can be exchanged effectively. We first assume that node encountering is known beforehand, and develop a max-flow based algorithm that obtains the optimal solution. While the assumption is clearly unrealistic, the optimal solution is useful to quantify the effectiveness of different heuristic algorithms. Specifically, we propose two network coding based heuristic algorithms. One algorithm uses full signaling where nodes exchange their coefficient matrix with each other while the other incur much less signaling overhead in that nodes only exchange rank information when meeting each

other. Both algorithms use a token based technique to limit the total number of transmissions, and only incur signaling at the beginning of a group meeting. Simulation results demonstrate that both algorithms achieve delays close to the minimum latency for moderate number of tokens. They present different trade offs in the number of transmissions and the signaling overhead.

1.6 Dissertation Organization

Chapter 2 will introduce our first method to solve electrical energy distribution in PHEV bus network. We define the problem to be solved clearly in section 2.1. Problem settings and solutions follow in section 2.2 and section 2.3. Simulation settings and results are shown in section 2.4.1 and section 2.4.2 to prove its way to reduce gas consumption.

Chapter 3 will show another approach to solve same problem that Chapter 1 involves. With changing system architecture, we will define a single storage on the bus network in section 3.1. Section 3.2 defines our design approach more specifically. Problem settings and optimal solution in section 3.4.1 and 3.3 will be presented. Results and outcomes are discussed at the end of Chapter 3 with including related work in section 3.5.

In Chapter 4 we introduce energy efficient packet transferring algorithms in delay tolerated network thus IOT. We introduce the network model and performance metrics considered in the section 4.1 and section 4.2. Section 4.3 presents the algorithm that obtains the minimum time to deliver a group of packets . We presents the two network coding based heuristic schemes in section 4.4. In section 4.5 also describes

performance evaluation. Section 4.6 includes related works.

Last, conclusions and future works are presented in Chapter 5.

Chapter 2

Optimal Renewable Energy Transfer via Electrical Vehicles

2.1 Introduction

Transportation is one of the major sources of environmental pollution that has challenged the sustainable growth of big cities all over the world [5]. Compared to conventional vehicles, electric vehicles (EVs) present many opportunities in improving energy efficiency and reducing greenhouse gas emissions, and hence have the potential to significantly reduce the environmental pollution caused by transportation. In addition, equipped with batteries and due to their built-in mobility, coordinated EVs can form a mobile and distributed energy storage system. Within the system, energy can be conveniently transported from place to place.

In our prior work [97], we propose a novel concept, *EV energy network*, for energy distribution and transmission using EVs. Specifically, an EV energy network consists

of a set of EVs and EV charge stations as well as an energy transportation network. The basic idea behind an EV energy network is that EVs transfer energy from renewable energy sources (e.g., solar or wind) to users who need energy (e.g., charging stations and houses) but do not have direct access to renewable energy sources. As an example, an EV can be charged by a renewable energy source and discharge energy at a charge station. Other EVs passing by the charge station can withdraw energy from the charge station, and hence indirectly use the energy from the renewable energy source. Analogous to a data communication network, the roads work as network links where energy flows, and charge stations work as routers that store and forward energy.

In this chapter, we investigate *optimal renewable energy transfer* in an EV energy network. Consider a bus transportation system in a city where all buses are hybrid EVs which can use both gas and electricity. Some buses have access to renewable energy sources on their routes, and hence can be charged directly by such sources, while the other buses can only indirectly use renewable energy through charge stations. Optimal renewable energy transfer determines how much energy an EV should deposit or withdraw at a charge station so that the total amount of renewable energy used by the bus system is maximized. We formulate and solve the above optimization problem using linear programming (LP). Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline scheme and provides an effective way to share renewable energy in a bus system, and hence can significantly reduce the environmental footprint of the bus system. Our results also demonstrate that a moderate battery size can realize most of the gains.

The rest of the Chapter 2 is organized as follows. We describe the problem setting in Section 2.2 and formulate and solve the optimization problem in Section 2.2 and

Section 2.3. We then evaluate the performance of our approach through extensive simulation in Section 2.4. At the end of the Chapter 2, related work is included in Section 3.5.

2.2 Problem Setting

Consider a bus transportation system in a city where all buses are EVs. Some bus routes have access to *renewable energy sources*, that generate electricity at a certain level (*e.g.* using solar or wind) and provide power to charge the battery of the buses running along these routes. A bus that is charged by renewable energy sources can discharge at a *charge station*, and hence transfer the renewable energy carried by its battery to the charge station, which can then charge other buses that pass by. In this way, renewable energy is transferred by a bus that has access to renewable energy sources to other buses that may not have direct access to renewable energy sources.

Fig. 2.2.1(a) shows a simple example, where the nodes represent bus stops. In particular the black node, node a , represents a renewable energy station (collocated with bus stop a), the yellow nodes, nodes b and c , represent charge stations, and the white nodes are ordinary bus stops. In this example, bus A has four bus stops, $\{a, b, c, d\}$, along its route. Since there is a renewable energy station at the first bus stop, *i.e.* node a , bus A can use the renewable energy source to charge its battery before starting its trip. While bus a travels along its route, it can deposit some energy at charge stations b and c . When bus B passes charge station b , it can withdraw energy, and hence get charged by renewable energy sources indirectly. Similarly, bus A can also deposit energy at charge station c , and the energy can be picked up by

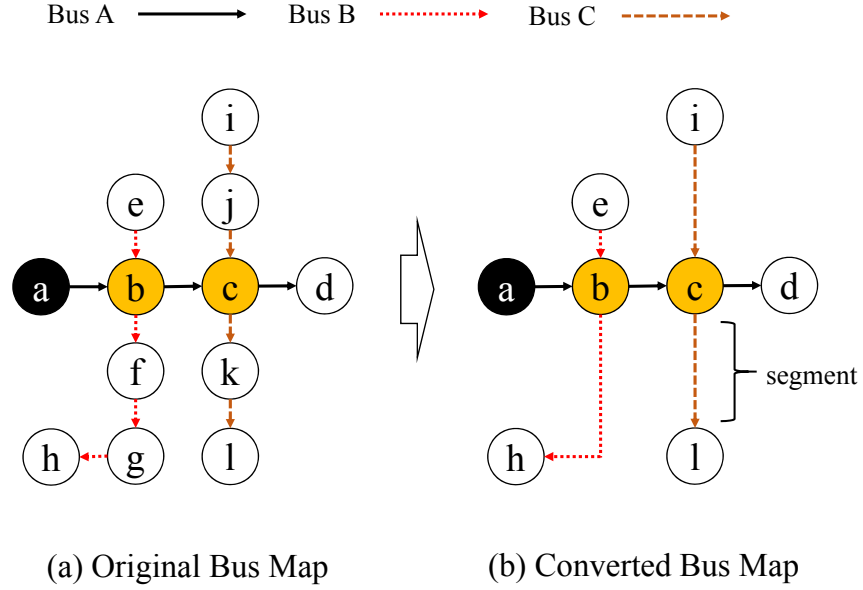


FIGURE 2.2.1: A simple example to illustrate renewable energy transfer in a bus system: (a) shows the original bus map with three buses traveling on three routes, and (b) shows the converted bus map for the ease of formulation.

bus C (when bus C arrives at bus stop c) at a later point of time.

In the example in Fig. 2.2.1(a), charge stations are placed at interchange points (bus stops) that connect two or more routes. We have studied charge station placement in [97]. Now with the locations of charge stations fixed, another important problem is how to transfer renewable energy effectively among buses. The total energy consumption (including both gas and electricity) for the periodic operation of the bus system is a constant. Our target is to maximize the electricity portion thus reduce the usage of gas. The decision variables are how much energy a bus should deposit to or withdraw from a charge station so that the total amount of renewable energy used by the bus system is maximized. As an example, suppose that in

Fig. 2.2.1(a), bus A can deposit a total of 10 units of energy at charge stations b and c ; bus B needs at least 7 units and bus C needs at least 3 units to finish their trip. Then the optimal solution is that bus A deposits 7 and 3 units of energy at charge stations b and c which will be picked up by bus B and C respectively. In practice, there can be a large number of buses and routes. In addition, two bus routes can share multiple charge stations and many buses may travel simultaneously along the same route (with different schedules).

2.3 Optimal Renewable Energy Transfer

Consider a time interval (*e.g.*, the time from the first bus starting operation to the last bus stopping operation in a day in a bus system). Let n_c denote the total number of charge stations. Let n_b denote the total number of buses running in the bus system. There can be multiple buses running along the same route but following different schedules (*e.g.*, the schedules of two buses are 30 minutes apart). These buses are treated independently. Similarly, a bus may start again after finishing a trip. For ease of formulation, the same bus that runs at different points of time is treated as different buses. We index the buses by $b = 1, \dots, n_b$. We assume that the schedules of the buses are known beforehand. In other words, we know exactly when a bus reaches a stop. In practice, the schedule of a bus may be dynamic, *e.g.*, due to traffic jams, detours, etc. In such scenarios, with the help of modern communication and positioning technologies (*e.g.*, GPS, cellular networks, etc.), the real-time information of the buses can be sent to a central server which can use the optimization formulation that we describe below (specifically the LP formulation) to

obtain the optimal schedule and transmit to the buses and charge stations.

For any bus b , let s_b denote the total number of charge stations on its route. It is easy to see that the route of bus b can be divided into $s_b + 1$ segments by the s_b charge stations. As illustrated in Fig. 2.2.1(b), we convert each route in the original bus map in Fig. 2.2.1(a) to contain multiple segments divided by the charge stations. For instance, in the converted map, the route for bus A contains three segments, while the routes for buses B and C both contain two segments. For the route of bus b , we index the charge stations by $c = 1, \dots, s_b$, and index the segments by $s = 0, \dots, s_b$. If a charge station is collocated with the first/last bus stop, then we treat the first/last segment as a virtual segment of zero length.

When a bus traverses a segment, it consumes either electricity or gas. Let $d_{b,s}$ denote the absolute amount of energy required for bus b to traverse segment s , and let $g_{b,s}$ and $h_{b,s}$ denote the amount of gas and electricity that bus b consumes when traversing segment s , respectively.

Therefore the objective function of optimal renewable energy transfer can be formulated as the following minimization problem:

$$\text{minimize: } \sum_{b=1}^{n_b} \sum_{s=0}^{s_b} g_{b,s} . \quad (2.3.1)$$

There are multiple constraints in the optimization problem as detailed below. First, for any bus b and any segment s , the summation of the gas consumption, $g_{b,s}$, and electricity consumption, $h_{b,s}$, should be equal to the absolute energy requirement for traversing the segment. That is,

$$g_{b,s} + h_{b,s} = d_{b,s} . \quad (2.3.2)$$

Let G_b be the capacity of the gas tank of bus b . The gas consumption, $g_{b,s}$, should be non-negative and limited by the capacity of the gas tank. That is,

$$0 \leq g_{b,s} \leq G_b. \quad (2.3.3)$$

In addition, for any bus b , it is reasonable to assume that the size of its gas tank is sufficiently large for the bus to finish the entire route. Hence,

$$G_b \geq \sum_{s=0}^{s_b} d_{b,s}. \quad (2.3.4)$$

Whenever a bus arrives at a charge station, it can either charge or discharge energy. Let $x_{b,c}$ denote the amount of energy that bus b charges/discharges at charging station c . We define $x_{b,c}$ to be negative when bus b discharges (deposits energy) to charge station c , and define $x_{b,c}$ to be positive when bus b gets charged (withdraws energy) from charge station c . The decision variables in our optimization problem are

$$x_{b,c}, \forall b = 1, \dots, n_b, \forall c = 1, \dots, n_c, c \neq 0. \quad (2.3.5)$$

Let B_b denote the battery capacity of bus b . Let $e_{b,s}$ denote the battery status (i.e., the amount of energy stored in the battery) of bus b at the beginning of segment s . Then clearly

$$0 \leq e_{b,s} \leq B_b, \forall s = 0, \dots, s_b. \quad (2.3.6)$$

After each energy exchange event, the battery status of bus b satisfies

$$e_{b,s+1} = e_{b,s} - h_{b,s} + x_{b,c_s}, \forall s = 0, \dots, s_b - 1, \quad (2.3.7)$$

where c_s is the index of the charge station at the end of segment s (or the beginning of segment $s + 1$). Specifically, the above equation states that the amount of energy stored in the battery of bus b at the beginning of segment $s + 1$ equals to the amount of energy at the beginning of segment s subtracted by the amount of electricity consumed when traversing segment s and the changes at charge station c_s .

Combining (3.3.4) and (3.3.6) yields a set of inequalities:

$$0 \leq e_0^b - \sum_{s=0}^m h_{b,s} + \sum_{s=0}^m x_{b,c_s} \leq B_b, \forall m = 0, \dots, s_b, \quad (2.3.8)$$

where e_0^b is the initial amount of energy in the battery of bus b . We define initial energy exchange for each bus is 0, $x_{b,0} = 0$.

For any charge station c , let b_c denote the number of buses that pass c . Whenever a bus passes a charge station, there is an energy exchange event. Therefore the total number of such events for any charge station is equal to the number of buses that pass it. We order the energy exchange events according to their occurring time, and let $y_{c,j}$ be the amount of energy that is transferred in the j th event at charge station c , for $j = 1, \dots, b_c$. Since the bus schedules are known beforehand, we know the indices of the energy exchange events beforehand. Suppose that the j th bus that passes charge station c is bus b , then $y_{c,j} = x_{b,c}$.

We assume the capacity of a charge station is sufficiently large, as charge stations usually can have much larger or more batteries installed compared to buses. Since the amount of energy withdrawn by a bus cannot exceed the amount of energy available at the charge station, for any charge station c we have

$$e_0^c - \sum_{i=1}^j y_{c,i} \geq 0, \forall j = 1, \dots, b_c, \quad (2.3.9)$$

TABLE 2.3.1: Notation used in problem formulation for decentralized solution.

Notation	Definition
n_b	The total number of buses
n_c	The total number of charge stations
s_b	The number of segments on the route of bus b
b_c	The number of buses that pass charge station c
e_0^b	Initial amount of energy in the battery of bus b
e_0^c	Initial amount of energy stored at charge station c
$x_{b,c}$	The amount of energy that bus b deposits (negative) or withdraws (positive) at charge station c
$d_{b,s}$	The energy requirement of traversing segment s for bus b
$g_{b,s}$	The amount of gas that bus b consumes in segment s
$h_{b,s}$	The amount of electricity that bus b consumes in segment s
$e_{b,s}$	The battery level of bus b at the beginning of segment s
$y_{c,j}$	The amount of energy of the j th energy transfer event at charge station c , $j = 1, \dots, b_c$
G_b	Capacity of the gas tank for bus b
B_b	Capacity of the battery for bus b
R	The set of routes with renewable energy stations

where e_0^c is the initial amount of energy in charge station c .

Last, let R be the set of routes with renewable energy stations. For simplicity, we assume the renewable energy station on a route is at the beginning of the route. Furthermore, for any bus running on such a route, we assume it gets fully charged at the beginning of the route. For a bus that runs on a route with no renewable energy source, we assume the initial energy stored in its battery is zero. Since B_b denotes the battery capacity of bus b , we have

$$e_0^b = B_b, \forall b \in R \text{ and } e_0^b = 0, \forall b \notin R.$$

In summary, the optimization problem is formulated in Fig. 3.3.2. It is a linear programming problem and can be solved using standard optimization tools (e.g., CVX

$$\text{minimize: } \sum_{b=1}^{n_b} \sum_{s=0}^{s_b} g_{b,s} \quad (2.3.10)$$

subject to:

$$G_b \geq \sum_{s=0}^{s_b} d_{b,s}, b = 1, \dots, n_b, \quad (2.3.11)$$

$$0 \leq g_{b,s} \leq G_b, s = 0, \dots, s_b, b = 1, \dots, n_b, \quad (2.3.12)$$

$$g_{b,s} + h_{b,s} = d_{b,s}, s = 0, \dots, s_b, b = 1, \dots, n_b, \quad (2.3.13)$$

$$0 \leq e_0^b - \sum_{s=0}^m h_{b,s} + \sum_{c=0}^m x_{b,c} \leq B_b, m = 0, \dots, s_b, \quad (2.3.14)$$

$$e_0^c - \sum_{i=1}^j y_{c,i} \geq 0, j = 1, \dots, b_c, c = 1, \dots, n_c, \quad (2.3.15)$$

$$e_0^b = B_b, \forall b \in R, e_0^b = 0, \forall b \notin R. \quad (2.3.16)$$

FIGURE 2.3.1: *Linear programming formulation for optimal renewable energy exchange*

[66]).

2.4 Performance Evaluation

2.4.1 Simulation Setting

Our performance evaluation uses the data set from Manhattan city bus system [64]. This bus system contains 40 bus routes that can be separated into eight independent components (each component contains a set of bus routes where a route shares at least one bus stop with at least another route; two components are independent when they do not share any bus stop). Since the energy transfers in

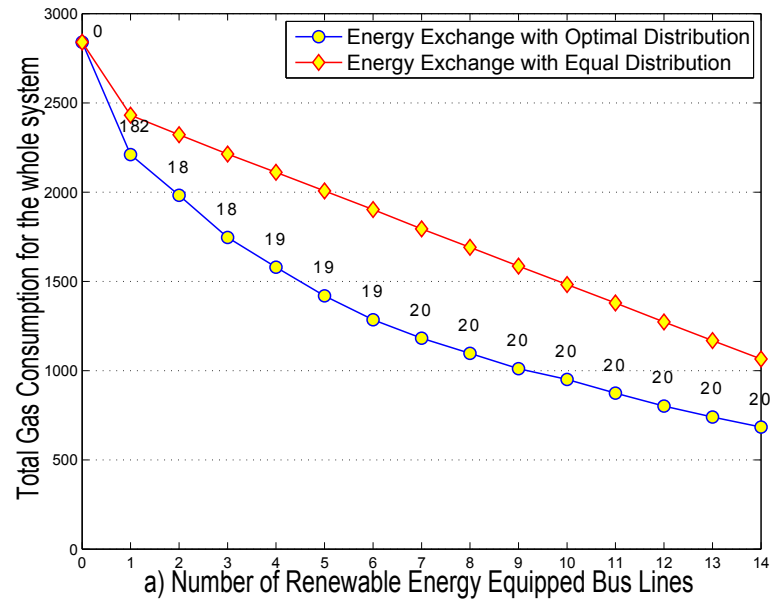


FIGURE 2.3.2: a) Performance comparison of the optimal and the baseline solutions by greedy placement algorithm

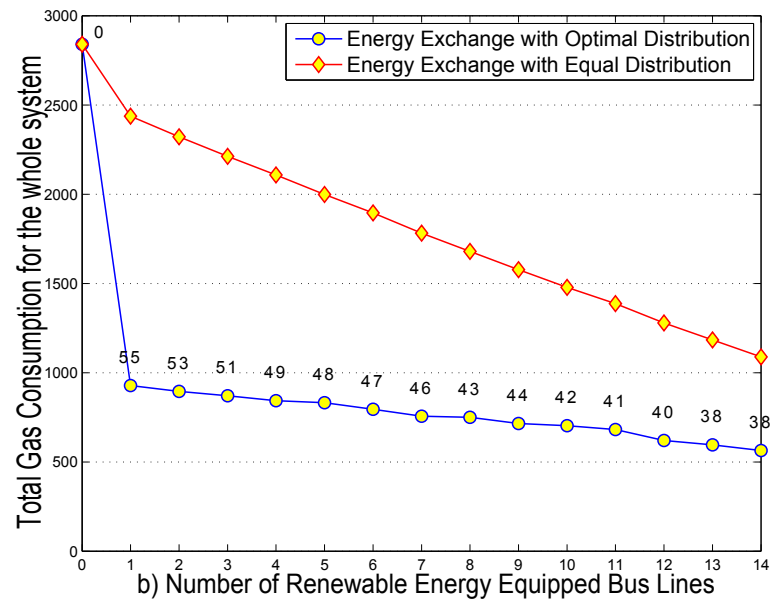


FIGURE 2.3.3: b) Performance comparison of the optimal and the baseline solutions by random placement algorithm

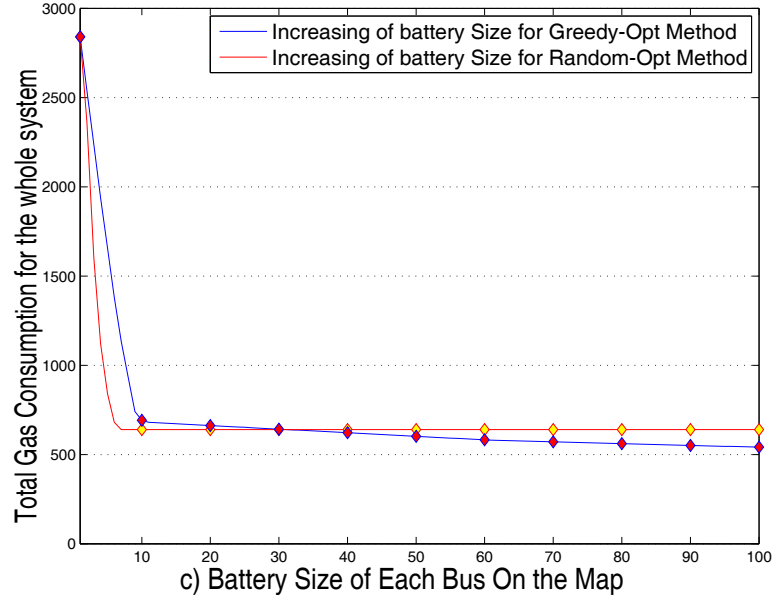


FIGURE 2.3.4: c) Impact of battery size by using optimal parameters for renewable energy lines and number of charge stations.

independent components are independent of each other, for simplicity, we only use the largest component in the rest of the chapter for performance evaluation. This component contains 104 bus stops on 28 different bus routes.

For simplicity, we assume on any route, traveling from one bus stop to the next bus stop requires one unit of energy. In the bus system we consider, the energy requirement of the longest route is 9 units. We assume a bus has a gas tank that can store 20 units of energy, and has a full tank of gas before starting its trip on a route. In addition, each bus is equipped with a battery that can store electrical energy. Electrical energy and gas energy will be used equivalently (i.e., traveling from one location to another requires the same amount of electrical and gas energy). Unless otherwise stated, we assume the battery of a bus can store 20 units of energy.

The energy transfer loss while exchanging energy is very low (less than 10% [97]).

For simplicity, we assume no energy transfer loss (the results are similar when assuming energy transfer loss of 10%). Also charging time is not considered since the technology is fast evolving and there are already commercial products that can charge very quickly [21]. A route has at most one renewable energy source. If it has a renewable energy source, for simplicity, we assume it is at the beginning of the route. A bus running on such a route is charged with a full battery of electrical energy by the renewable energy source before starting the trip.

For each route, we assume 20 buses traveling along the route. The schedule of the buses are known beforehand. Specifically, the first bus starts at time 0 and the next one leaves 30 minutes afterwards, and so on. We assume charge stations are placed at bus stops and the capacity of a charge station is sufficiently large. Charge stations should be placed so that the number of charge stations is minimized and buses on a bus route that does not have a renewable energy source can indirectly use renewable energy through charge stations. We use the two schemes, greedy and random schemes, proposed in our prior work [97] for charge station placement. Specifically, the greedy scheme picks a bus stop from the map that covers the largest number of bus lines as a charge station and adds it to a list. It then removes those bus routes (include their bus stops) from the map. It repeats the process until each bus route has at least one charge station. The random scheme differs from the greedy scheme in that it picks a bus stop randomly. More details of these two schemes can be found in [97].

We compare the performance of our proposed scheme with a baseline scheme. In the baseline scheme, a bus that is charged by a renewable energy source deposits the energy not used in its trip evenly to the charge stations along its route. In addition, when a bus that is not charged directly by a renewable energy source (*i.e.*, a bus that runs along a route without a renewable energy source) passes a charge

station, it is charged as much as possible. The performance metric we use is the total gas consumption of all the buses. We randomly choose routes as the routes with renewable energy sources. The number of such routes is varied from 1 to 14. For each setting, we make 100 simulation runs (by using independent random seeds to choose the routes that have renewable energy sources) and obtain the average gas consumption along with 95% confidence interval. For each setting, we use CVX [66] tool box for MATLAB 2013 [80] to solve our optimization problem.

2.4.2 Evaluation Results

Fig. 2.3.2 plots the total gas consumption when charge stations are placed using the greedy scheme [97]. The results of both the optimal solution and the baseline solution are plotted in the figure. For each setting, the result is the average over 100 simulation runs (the 95% confidence intervals are tight and hence omitted from the figure). The numbers above the performance curve represent the average number of charge stations over 100 runs (rounded to the closest integer). (The optimal solution and the baseline scheme are compared under the same settings; hence we only mark the numbers of charge stations on one performance curve.) We observe that, as expected, the total amount of gas consumption decreases when increasing the number of routes that have renewable energy sources. The optimal solution leads to much more reduction than the baseline scheme. Specifically, when the number of routes with renewable energy sources is 14, the amount of gas consumption is reduced to 26% under the optimal solution (from 2840 to 740 units of energy) and is reduced to 41% under the baseline scheme. The amount of gas consumption under the optimal solution is 36.8% less than the baseline scheme. Assuming CO_2 is only generated

during gas consumption in our system, the amount of CO_2 emission is also reduced to 26% under the optimal solution.

Fig. 2.3.3 plots the results when charge stations are placed using the random scheme [97]. We observe similar trend as that in Fig. 2.3.2. Since more charge stations are used when using random charge station placement, for the same energy transfer scheme (i.e., the optimal solution or baseline scheme) and the same number of routes with renewable energy sources, the total gas consumption may be even lower in Fig. 2.3.3 than that in Fig. 2.3.2.

The results presented above assume the battery size of each bus can store 20 units of energy. We next vary the battery size and investigate its impact on total gas consumption. Fig. 2.3.4 plots the results when using the optimal solution for energy transfer and 14 routes have renewable energy sources. Again each result is the average of 100 simulation runs (the 95% confidence intervals are tight and hence omitted) by randomly choosing routes to have renewable energy sources. The results of both charge station placement strategies are plotted in the figure. We observe a diminishing gain of battery size. Specifically, as the battery size increases from 1 to 100 units, the total gas consumption reduces dramatically at the beginning and decreases slowly afterwards. For both greedy and random charge station placement strategies, a modest battery size (in our case 10 unit) is sufficient to realize most of the performance gains.

2.5 Related Work

The study closest to ours is [97] that proposes the concept of EV energy network and proposes two algorithms for charge station placement. Our study solves an important problem in EV energy networks, namely how to optimally transfer renewable energy through EVs. The study in [98] develops a hypergraph based approach to reduce the sum of all route hops from renewable energy sources to charge stations, which differs in scope from our study. Several studies are on scheduling the charging of EVs [27, 46, 60, 65, 73, 79, 91]. These studies focus on when to charge an EV from the power grid, while our study focuses on renewable energy transfer by developing an optimal solution that determines how much energy an EV should charge or discharge at a charge station. Broadly, our study is related to vehicle-to-grid [85], where vehicles store energy and transfer energy to the power grid. Our focus is however energy transfer among EVs through charge stations, which differs significantly from general vehicle-to-grid.

Chapter 3

Optimal Centralized Renewable Energy Transfer Scheduling for Electrical Vehicles

3.1 Introduction

Air pollution is a key challenge for industrial countries around the world. In the United States, transportation is one of the largest causes of air pollution [37]. Plug-in hybrid electrical vehicle (PHEV) that can use both gas and electricity is an attractive alternative technology that has the potential to significantly reduce air pollution from vehicles. In addition, with their batteries and mobility, PHEVs can form a distributed energy network where energy can be conveniently transported from place to place [97].

Our previous work [12] considers a bus transportation system in a city where all buses are PHEVs and a number of charge stations serve as energy exchange points (i.e., a bus can deposit or withdraw energy at a charge station). Some buses have

access to renewable energy sources on their routes, and hence can be charged directly by such sources. A bus charged by a renewable energy source can discharge energy at a charge station; another bus passing by the charge station can withdraw energy from the charge station, and hence indirectly use the energy from the renewable energy source. We formulate an optimal energy transfer problem, which determines how much energy a bus should deposit or withdraw at a charge station so that the total amount of renewable energy used by the bus system is maximized.

The above formulation assumes that each charge station is equipped with large energy storage (battery) to serve as an energy exchange point. This assumption, however, may not be feasible in practice because installing large batteries at the charge stations can be cost prohibitive [4]. This is especially true in metropolitan areas, where a large number of charge stations are needed.

In Chapter 3, instead of using multiple energy storages that are distributed at the charge stations, we assume that there is only a *single* centralized energy storage. The infrastructure is underground, where some *charging points* have underground cables connected to the central energy storage (CES), and a central controller controls the energy exchanges between the PHEVs and the CES via the charging points. This is reasonable since many large cities already have tunnels and places for underground cables in their subterranean metro systems [68]. In addition, recent advances in Boolean Microgrids [63] allow for discrete power delivery and fully digital control mechanism that are needed in our system. We assume that renewable energy sources generate energy and store it in the CES. PHEVs can withdraw energy from the CES and hence indirectly use renewable energy sources when stopping at the charging points. The capacity of the CES is limited. Hence energy generated by the renewable energy sources can be wasted when it exceeds the capacity of the CES. On the other

hand, each PHEV has a battery, and hence the PHEVs naturally form a distributed energy network that can help to store the energy from the CES to reduce energy waste. An interesting question is how to schedule charging or discharging events for the PHEVs to reduce energy waste at the CES while maximizing the total amount of renewable energy used by PHEVs. We develop an optimization based approach to solve this problem using linear programming. Simulation results using the Manhattan city bus system demonstrate that our approach significantly outperforms a baseline strategy. In addition, since our approach uses the batteries of the PHEVs efficiently, only a small battery at the CES is sufficient to realize most of the gains.

The rest of the chapter is organized as follows. We first present the architecture of the system in Section 3.2. Problem formulation and solution are given in Section 3.3. We then present simulation setting and results in Section 3.4. We briefly describe related work in Section 3.5

3.2 System Architecture

Consider a bus transportation system that consists of buses and bus stops. Buses are PHEVs that can use both gas and electricity. Some bus stops are charging points that have special equipment to exchange electricity with a bus when the bus stops at the charging point. The charging points do not have any electrical battery onboard. Instead, they are connected to a central energy storage (CES) using underground cables that allow energy/electricity to flow through. The CES gets energy from renewable energy sources such as solar and wind. Through the charging points, the buses can get electricity from the CES, and thus use renewable energy.

A central control system (CCS) is responsible for orchestrating electricity exchanges between buses and the CES through the charging points. Specifically, it decides how much energy a bus withdraws from or deposits into the CES at a charging point. The goal is to maximize the electricity that is used by the buses, and thus minimizing the usage of gas (since the total energy consumption, including both gas and electricity, of the bus system is a constant). The CCS arranges energy exchange using Boolean Microgrid technology [63] that allows transmitting electricity as discrete packets. Therefore, multiple charging events between buses and charging points can happen simultaneously. The buses, charging points, CES and CCS are equipped with communication devices (e.g., Wi-Fi, cellular devices), and can communicate with each other in real-time. For instance, when a bus is delayed due to traffic jams, it can send its current schedule to the CCS. Similarly, the CCS can send its decision on how much to charge or discharge at a charging point to a bus in real-time.

Fig. 3.2.1 shows the high-level architecture of the system. It depicts two layers. The upper layer shows the main components and the information flow among the various components. Specifically, information is transmitted in two directions: in one direction, the CCS sends decisions and signals to the buses, charging points, and CES; in the other direction, the buses, charging points, and CES send their current status to the CCS. For clarity, the information flow is not marked explicitly in the figure; rather it is implicitly marked by the radio waves (representing wireless communication) at the various components. The lower layer shows the underground cables and the energy flow between the CES and the charging points.

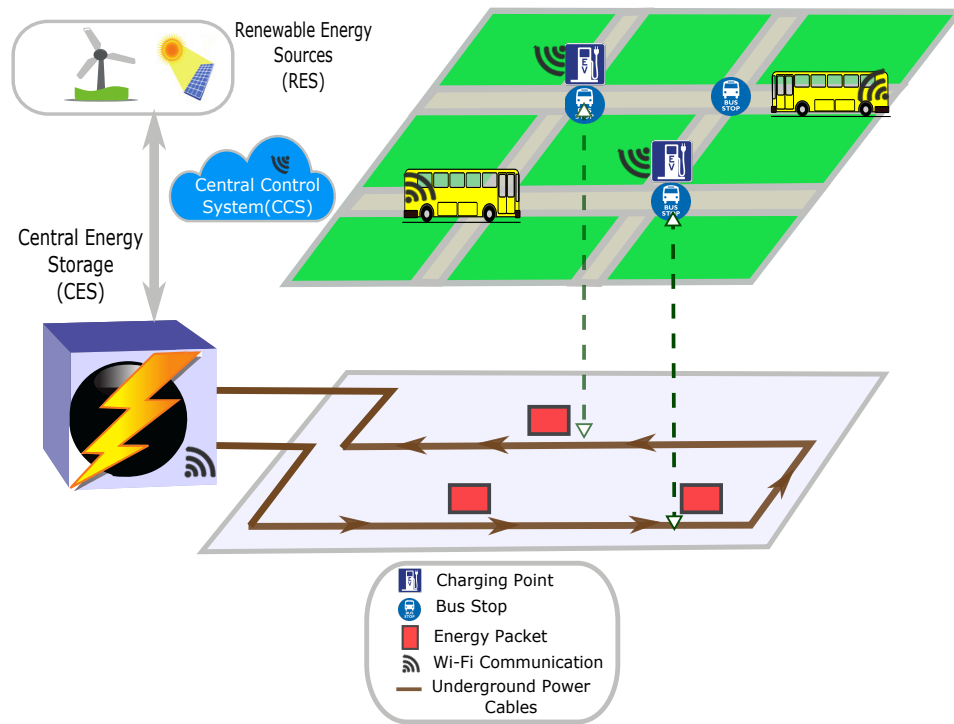


FIGURE 3.2.1: High-level architecture of the system.

3.3 Optimal Centralized Energy Transfer

In this section, we present an optimization based approach that determines the optimal solution for energy transfer between the CES and the buses through the charging points. For ease of exposition, we first assume that the CCS knows the system information (bus schedules and renewable energy generation at the CES) beforehand (see Section 3.3.1). When this is not the case, i.e., the bus schedules can change due to traffic or road conditions, or the renewable energy generation at the CES may deviate from the prediction, we describe how the CCS dynamically adjusts the decisions based on real-time information provided by the buses and CES (see Section 3.3.2).

3.3.1 System information known beforehand

In this setting, we assume that the buses run according to their schedules, and the renewable energy generation at the CES can be accurately predicted based on historical data. In addition, the above information is known by the CCS beforehand. Therefore, the CCS solves an optimization problem that determines the optimal charging and discharging decision for each bus at the charging points. We next describe the optimization formulation.

Let n denote the total number of buses that run in the bus system during a time interval (e.g., the time from when the first bus starts operation to when the last bus stops operation in a day). There can be multiple buses running along the same route, each following a different schedule. For ease of exposition, we treat the buses independently and index the buses by $b = 1, \dots, n$.

Since our problem mainly concerns how much energy a bus needs to deposit or

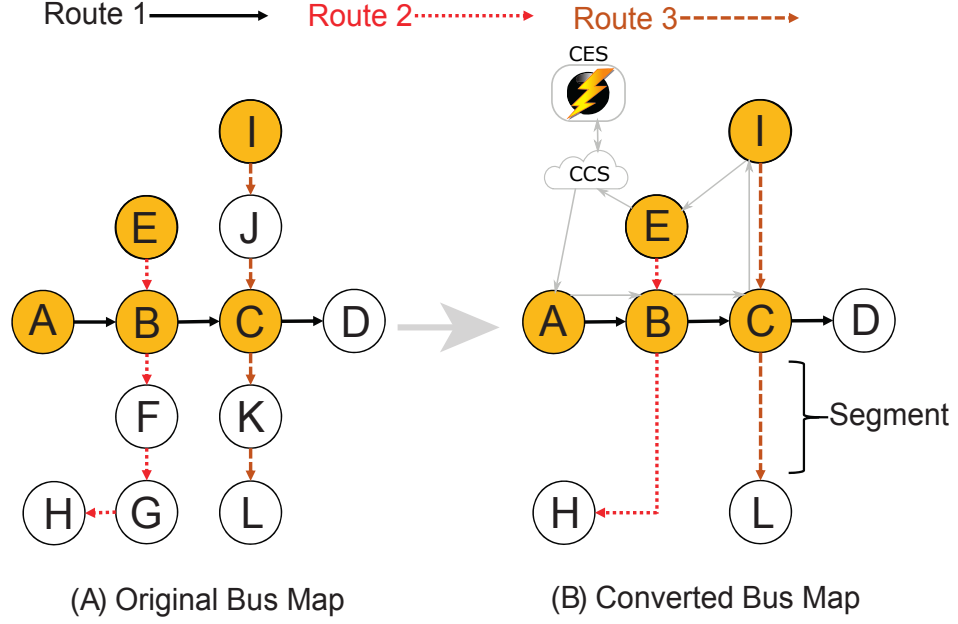


FIGURE 3.3.1: A simple example: (a) shows the original bus map with three bus routes, and (b) shows the converted bus map for ease of formulation.

withdraw at a charging point, it is sufficient to focus on the charging points instead of individual bus stops. For any bus b , let s_b denote the total number of charging points on its route. It is easy to see that the route of bus b can be divided into $s_b + 1$ segments, indexed by $0, \dots, s_b$. If a charging point is collocated with the first/last bus stop, then we treat the first/last segment as a virtual segment of zero length. Fig. 3.3.1 shows an example. Fig. 3.3.1(a) shows the original bus map and Fig. 3.3.1(b) shows the converted map. In the original map, the orange nodes, A, E, I, B , and C , represent charging points; the white nodes represent bus stops that are not charging points. Route 1 has three charging points, and Routes 2 and 3 both have two charging points. In the converted map, Route 1 has four segments, Routes 2 and 3 both have three segments, and the first segment of all three routes is a virtual segment of zero length.

When a bus travels, it consumes either electricity or gas. Let $d_{b,s}$ denote the

total amount of energy required for bus b to traverse segment s . Let $g_{b,s}$ and $h_{b,s}$ denote the amount of gas and electricity that bus b consumes when traversing segment s , respectively. As discussed earlier, our goal is to maximize the total amount of electrical energy (i.e., minimize the total amount of gas) that is used by the bus system. Hence, the objective function of optimization problem can be described as

$$\text{minimize: } \sum_{b=1}^n \sum_{s=0}^{s_b} g_{b,s} . \quad (3.3.1)$$

We next describe the constraints in the optimization problem. First, for any bus b in any segment s , the summation of the gas consumption, $g_{b,s}$, and electricity consumption, $h_{b,s}$, should be equal to the energy requirement for traversing the segment. That is,

$$g_{b,s} + h_{b,s} = d_{b,s} . \quad (3.3.2)$$

Let G_b be the capacity of the gas tank of bus b . The gas consumption, $g_{b,s}$, should be non-negative and limited by the capacity of the gas tank. In addition, for any bus b , it is reasonable to assume that the size of its gas tank is sufficiently large for the bus to finish the entire route. Hence,

$$0 \leq g_{b,s} \leq G_b , \quad \sum_{s=0}^{s_b} d_{b,s} \leq G_b . \quad (3.3.3)$$

Let B_b denote the battery capacity of bus b . Let $e_{b,s}$ denote the battery status (i.e., the amount of energy stored in the battery) of bus b at the beginning of segment s . Then clearly

$$0 \leq e_{b,s} \leq B_b, \forall s = 0, \dots, s_b. \quad (3.3.4)$$

When bus b arrives at the beginning of segment s (which is a charging point), it can either charge or discharge energy. Suppose the fraction of energy loss for an energy exchange event (charging or discharging) is λ , $0 \leq \lambda < 1$. If the amount of energy that a bus obtains is x , then taking account of the energy loss, the amount of energy at the CES is reduced by $x/(1 - \lambda)$. Similarly, if the amount of energy that a bus deposits is y , then taking account of the energy loss, the actual amount of energy that the CES obtains is $(1 - \lambda)y$. To differentiate the charging and discharging events, we define two variables, $x_{b,s}$ and $y_{b,s}$, that denote respectively the amount of energy that bus b obtains or deposits at the beginning of segment s . As an example, if bus b gets charged by the CES by 10 units of energy, then $x_{b,s} = 10$ and $y_{b,s} = 0$; if bus b discharges 10 units of energy to the CES, then $x_{b,s} = 0$ and $y_{b,s} = 10$. Correspondingly, the amount of energy reduced at the CES is $10/(1 - \lambda)$ for the former event, while the amount of energy increased at the CES is $10 \times (1 - \lambda)$ for the latter event.

We next describe the constraints for $x_{b,s}$ and $y_{b,s}$. Let C denote the storage capacity of the CES. Let E_t denote the amount of energy at the CES at time t . Let $t_{b,s}$ denote the time of the energy exchange event (i.e., the time for bus b to reach the beginning of segment s). The amount of energy that bus b obtains cannot exceed its remaining battery storage and the amount of energy at the CES (taking account of the energy loss). That is,

$$0 \leq x_{b,s} \leq \min((1 - \lambda)E_{t_{b,s}}, B_b - e_{b,s}) \quad (3.3.5)$$

Similarly, the amount of energy that bus b deposits cannot exceed the amount of energy in its battery and the remaining storage of the CES (taking account of the

energy loss). That is,

$$0 \leq y_{b,s} \leq \min \left(\frac{C - E_{t_{b,s}}}{1 - \lambda}, e_{b,s} \right) \quad (3.3.6)$$

The amount of energy stored in the battery of bus b at the beginning of segment $s + 1$ equals to the amount of energy at the beginning of segment s subtracted by the amount of electricity consumed when traversing segment s and the changes at the beginning of segment s . Therefore, the evolution of the battery status of bus b is

$$e_{b,s+1} = e_{b,s} - h_{b,s} + x_{b,s} - y_{b,s}, \forall s = 0, \dots, s_b - 1 \quad (3.3.7)$$

Combining (3.3.4) and (3.3.7), we have that for bus b and any segment $m = 0, \dots, s_b$,

$$0 \leq e_{b,0} - \sum_{s=0}^m h_{b,s} + \sum_{s=0}^m x_{b,s} - \sum_{s=0}^m y_{b,s} \leq B_b, \quad (3.3.8)$$

where $e_{b,0}$ is the initial amount of energy in the battery of bus b , $x_{b,0} = 0$ and $y_{b,0} = 0$ (since segment 0 is the segment before the first charging point). The decision variables in our optimization problem are $x_{b,s}$ and $y_{b,s}$, $b = 1, \dots, n$, $s = 1, \dots, s_b - 1$.

We refer to an event that a bus reaches a charging point and needs to decide how much to exchange with the CES as an energy exchange event. Let the total number of energy exchange events at the CES be N . Suppose that the j th energy exchange event corresponds to the event that bus b withdraws or deposits energy at the beginning of segment s . Let u_j and v_j denote respectively the amount of energy for these two types of events (relative to the CES). Since $x_{b,s}$ and $y_{b,s}$ denote respectively the amount of energy that bus b obtains and deposits into the CES corresponding these two events, then taking account of energy loss, we have $u_j = x_{b,s}/(1 - \lambda)$ and $v_j = (1 - \lambda)y_{b,s}$.

TABLE 3.3.1: Notation used in problem formulation for centralized solution.

Notation	Definition
n	Total number of buses
s_b	Number of charging points on the route of bus b
$d_{b,s}$	Energy requirement of traversing segment s for bus b
$g_{b,s}$	Amount of gas that bus b consumes in segment s
$h_{b,s}$	Amount of electricity that bus b consumes in segment s
$x_{b,s}$	Amount of energy that bus b obtains at the beginning of segment s
$y_{b,s}$	Amount of energy that bus b deposits at the beginning of segment s
$e_{b,s}$	Battery status of bus b at the beginning of segment s
$t_{b,s}$	Time that bus b is at the beginning of segment s
λ	Fraction of energy loss during an energy exchange event
G_b	Capacity of the gas tank for bus b
B_b	Capacity of the battery for bus b
E_t	Amount of energy in the CES at time t
C	Capacity of the CES
N	Total number of energy exchange events at the CES

Since at any point of time, the amount of energy at the CES should be no more than its capacity, we need to have that for any $j = 1, \dots, N$,

$$0 \leq E_0 - \sum_{i=1}^j u_i + \sum_{i=1}^j v_i + R_j - L_j \leq C, \quad (3.3.9)$$

$$0 \leq L_j, \quad (3.3.10)$$

where E_0 denotes the initial energy at the CES at time 0, R_j denotes the amount of renewable energy that has been generated by the renewable energy sources up to the time when the j th event happens, and $L_j \geq 0$ denotes the amount of energy wasted at the CES (because of the limited storage of the CES). As mentioned earlier, R_j is known beforehand, while L_j is a decision variable.

Table 3.3.1 summarizes the key notation for easy references. The optimization

problem is formulated in Fig. 3.3.2. Note that by definition, we should have $x_{b,s} \times y_{b,s} = 0$, and similarly $u_i \times v_i = 0$. The formulation in Fig. 3.3.2 does not contain these two constraints. This is because with energy loss during energy exchange, violating these two constraints leads to sub-optimal solutions. Therefore there is no need to include them explicitly. The formulation is a linear programming problem and can be solved using standard optimization tools (e.g., CVX [66]).

3.3.2 System information not known beforehand

In the above, we have assumed that the bus schedules and the amount of renewable energy generation are known beforehand. In practice, due to various traffic and road conditions (e.g., traffic jams, road constructions, detours, etc.), the schedule of a bus can be affected significantly, and hence affecting the timing of the relevant events and the optimal solution. Similarly, the prediction of the renewable energy generation at the CES may not be accurate. In such cases, the communication capability of the system allows real-time update to the CCS. The CCS in turn recalculates the optimal solution based on the updated information using the same approach as described earlier. Specifically, suppose that bus b detects a significant delay at time T . It then estimates the arriving time to the subsequent charging points on its route, and transmits the information through the communication infrastructure to the CCS. The CCS then solves an optimization problem as in Fig. 3.3.2 for $t \geq T$ only (the values of the various variables for $t < T$ are given as in the original optimal solution), and sends the solution to the buses. The above approach can be easily realized in practice because many cities already have early delay detection systems (e.g., New York City MTA [64]) and solving a linear programming problem is very fast on modern

$$\text{lll minimize: } \sum_{b=1}^n \sum_{s=0}^{s_b} g_{b,s} \quad (3.3.11)$$

subject to:

$$0 < \sum_{s=0}^{s_b} d_{b,s} \leq G_b, b = 1, \dots, n, \quad (3.3.12)$$

$$0 \leq g_{b,s} \leq G_b, s = 0, \dots, s_b, b = 1, \dots, n, \quad (3.3.13)$$

$$g_{b,s} + h_{b,s} = d_{b,s}, s = 0, \dots, s_b, b = 1, \dots, n, \quad (3.3.14)$$

$$0 \leq x_{b,s} \leq \min((1 - \lambda)E_{tb,s}, B_b - e_{b,s}), b = 1, \dots, n, \\ s = 0, \dots, s_b \quad (3.3.15)$$

$$0 \leq y_{b,s} \leq \min\left(\frac{C - E_{tb,s}}{1 - \lambda}, e_{b,s}\right), \\ b = 1, \dots, n, s = 0, \dots, s_b \quad (3.3.16)$$

$$0 \leq e_{b,0} - \sum_{s=0}^m h_{b,s} + \sum_{s=0}^m x_{b,s} - \sum_{s=0}^m y_{b,s} \leq B_b, \\ b = 1, \dots, n, m = 0, \dots, s_b \quad (3.3.17)$$

$$0 \leq E_0 - \sum_{i=1}^j u_i + \sum_{i=1}^j v_i + R_j - L_j \leq C, j = 1, \dots, N \quad (3.3.18)$$

$$0 \leq L_j, j = 1, \dots, N \quad (3.3.19)$$

FIGURE 3.3.2: Linear programming formulation for optimal renewable energy exchange computers.

3.4 Performance Evaluation

3.4.1 Simulation Setting

Our performance evaluation uses the data set from Manhattan city bus system [64]. This bus system contains 40 bus routes divided by eight independent components (each component contains a set of bus routes where a route shares at least one bus

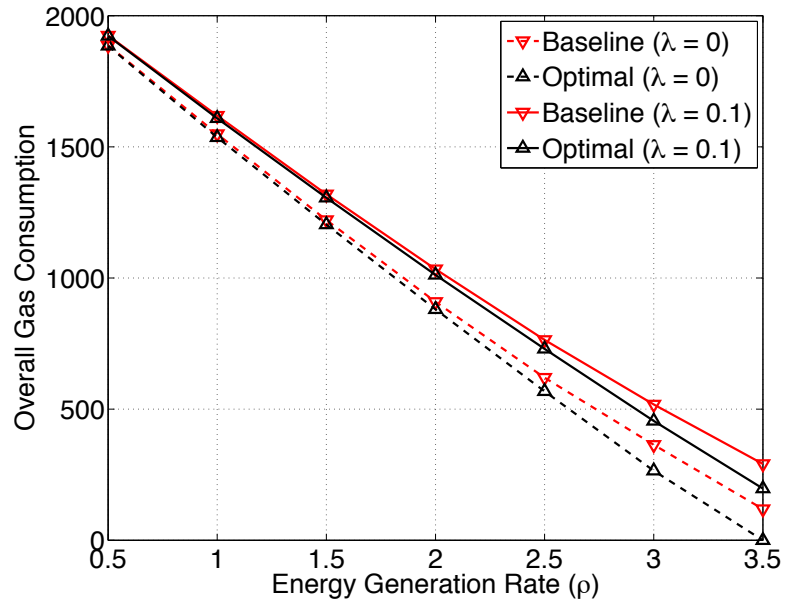


FIGURE 3.4.1: The amount of gas consumption when the capacity of the CES is 20 units of energy (i.e., $C = 20$)

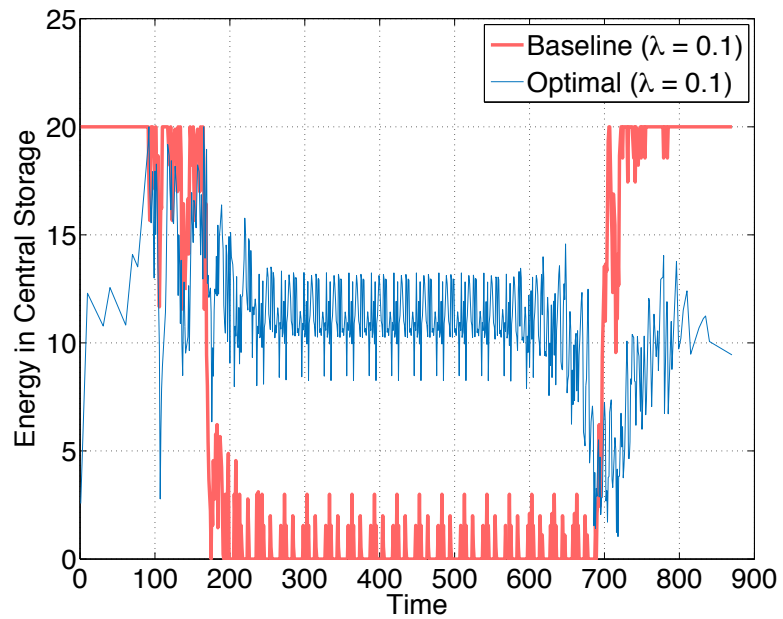


FIGURE 3.4.2: The amount of energy in the CES over time, $C = 20$, $\rho = 3$, $\lambda = 0.1$.

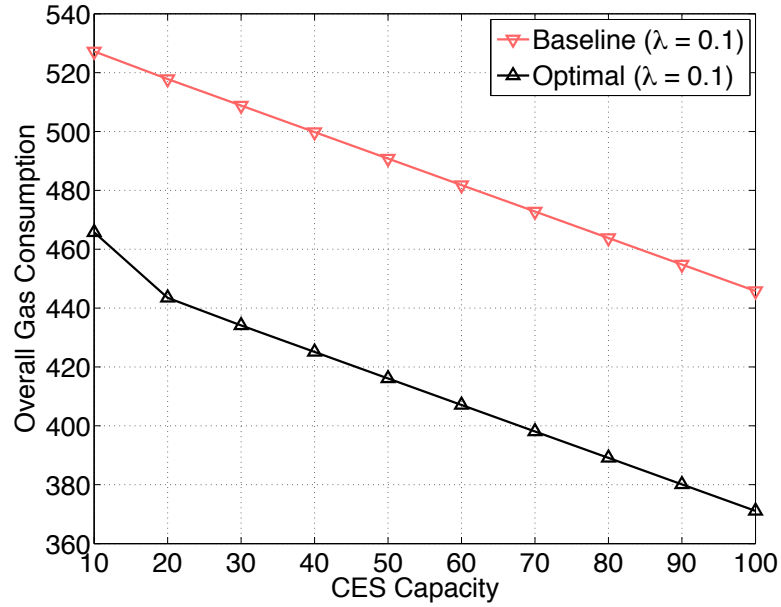


FIGURE 3.4.3: The impact of the capacity of the CES on the total gas consumption, $\rho = 3$ and $\lambda = 0.1$.

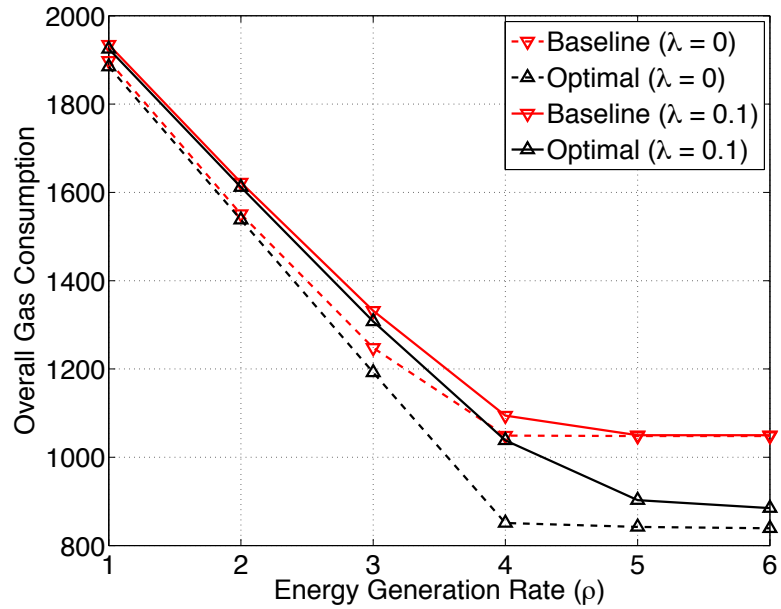


FIGURE 3.4.4: The amount of gas consumption when the capacity of the CES is 20 units of energy (i.e., $C = 20$, half day energy generation).

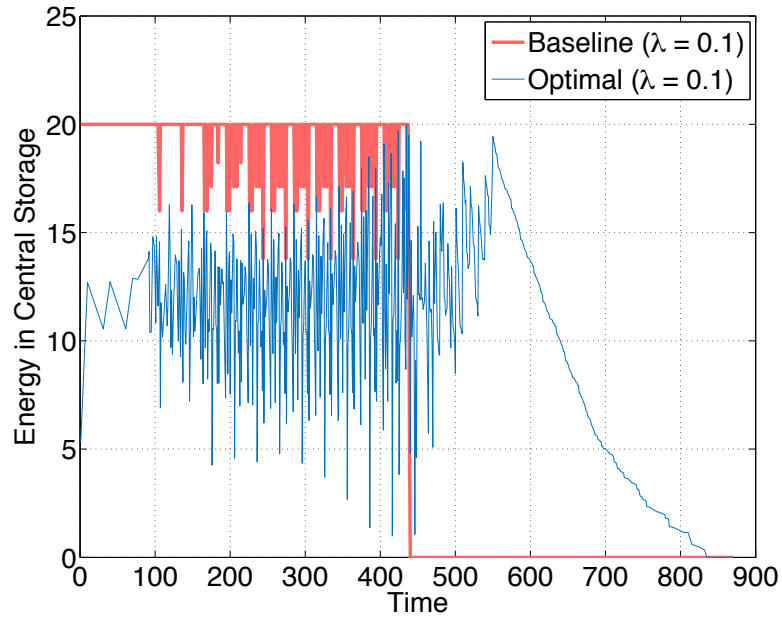


FIGURE 3.4.5: The amount of energy in the CES over time, $C = 20$, $\rho = 6$, $\lambda = 0.1$, half day energy generation.

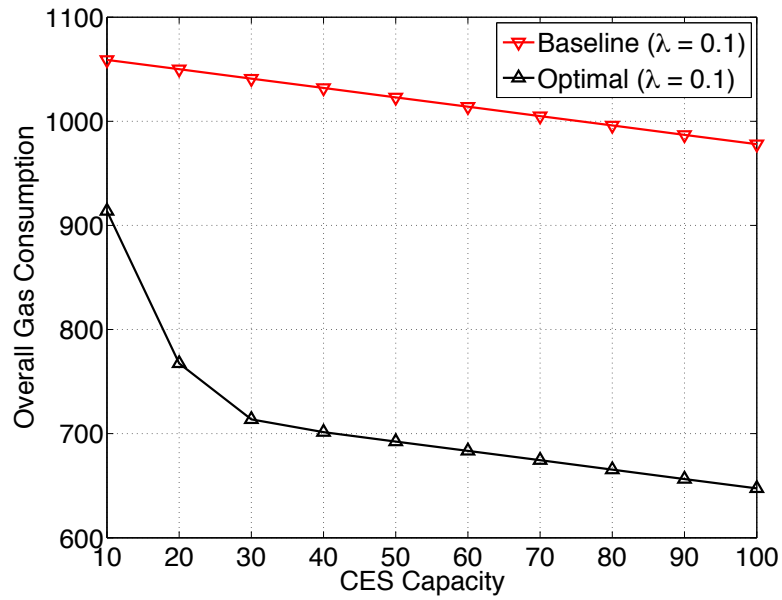


FIGURE 3.4.6: The impact of the capacity of the CES on the total gas consumption, $\rho = 6$ and $\lambda = 0.1$, half day energy generation.

stop with at least another route; two components are independent when they do not share any bus stop). For simplicity, we consider only the largest component that contains 104 bus stops on 28 different bus routes. For each route, we assume 20 buses traveling along the route. The bus schedules are known beforehand; the case when the bus schedules change over time can be solved as outlined in Section 3.3.2.

We assume that on each route, traveling from one bus stop to the next requires one unit of energy. In the bus system, the energy requirement of the longest route is 9 units. We assume a bus has a gas tank that can store 10 units of energy, and has a full tank of gas before starting its trip on a route. In addition, each bus is equipped with a battery that can store electrical energy. Electricity and gasoline will be consumed equivalently (i.e., traveling from one location to another requires the same amount of electrical and gas energy). We assume the battery of a bus can store 10 units of electrical energy, and the initial battery level is zero.

We assume 10% energy loss during energy exchange [97], i.e., $\lambda = 0.1$. Charging time is not considered since the technology is fast evolving and there are already commercial products that can charge very quickly [3]. A route can have multiple charging points located at the bus stops. For every route, we set the first bus stop to be a charging point. We then find the most visited bus stop (i.e., the one traversed by most bus routes), set it as a charging point and remove the bus routes that traverses the bus stop from the map. This process is repeated until every bus route has at least one charging point.

For the CES, we assume the energy generation of the renewable energy sources is at an average rate of ρ units of energy per time unit. We consider two scenarios of energy generation. In the first scenario, energy is generated throughout the simulation time. In the second scenario, considering the intermittent energy generation of renewable

energy sources, energy is only generated in the first half of the simulation time. For both cases, we assume the energy generation profile is known beforehand. When this is not the case, the problem can be solved as outlined in Section 3.3.2. We vary the capacity of the CES from 10 to 100 and investigate its impact on the amount of gas consumption of the bus system.

The performance metric is the total gas consumption of the buses. We compare the performance of our proposed solution with a baseline scheme. The baseline scheme works in a greedy manner. Specifically, when a bus stops at a charging point, it checks the amount of energy in its battery. If the amount of energy is not sufficient for it to finish its route, it tries to get as much energy as needed from the CES.

3.4.2 Evaluation Results

Fig. 3.4.1, Fig. 3.4.2 and Fig. 3.4.3 plot the simulation results for the scenario where the renewable energy sources generate energy at an average rate of ρ throughout the simulation time (from 0 to 870 time units). Fig. 3.4.1 plots the amount of gas consumption of the optimal and baseline schemes when the CES can store 20 units of energy, and the energy generation rate, ρ , varies from 0.5 to 3.5 units of energy per time unit. The results when the fraction of energy loss $\lambda = 0.1$ and the results for the idealized case where there is no energy loss (i.e., $\lambda = 0$) are both shown in the figure. We observe that the difference of the optimal and the baseline schemes is small when ρ is small, and becomes much more dramatic as ρ increases. For instance, when $\lambda = 0.1$, the optimal scheme consumes around 3% less gasoline than the baseline scheme for $\rho = 2$; for $\rho = 3.5$, the saving from the optimal scheme compared to the baseline scheme becomes 32%. This is because when energy is generated at a higher rate,

the optimal scheme uses the generated energy more efficiently by optimally taking advantage of the batteries of the buses. Specifically, unlike the baseline scheme, a bus in the optimal scheme may take significantly more energy than it needs to finish the route to temporarily store the energy for the CES (and discharge it later to the CES) to reduce the amount of energy overflow at the CES. It may also take significantly less energy than needed (and take more energy later on) so that other buses can share the energy stored at the CES. We observe similar results under the idealized case when $\lambda = 0$. The difference between the optimal and baseline schemes is slightly less when $\lambda = 0.1$ compared to that when $\lambda = 0$. This is because when $\lambda = 0.1$, some energy is lost when a bus deposits energy back to the CES in the optimal scheme, while in the baseline scheme, a bus never deposits energy back to the CES.

Fig. 3.4.2 plots the energy level of the CES over the time when $\rho = 3$, $\lambda = 0.1$ and the capacity of the CES is 20. We observe that the energy level of the CES is much more stable under the optimal scheme than that under the baseline scheme. For the baseline scheme, the amount of energy of the CES quickly reaches the capacity, and then decreases to very low values (because each bus greedily takes as much energy as needed). The much more stable energy level of the CES under the optimal scheme confirms that the optimal scheme uses the distributed energy storage of the buses more efficiently. Fig. 3.4.3 plots the overall gas consumption of the two schemes when the capacity of the CES increases from 10 to 100, when $\rho = 3$ and $\lambda = 0.1$. As expected, the amount of gas consumption reduces for both schemes when the capacity of the CES increases.

Fig. 3.4.4, Fig. 3.4.5 and Fig. 3.4.6 plots the simulation results when the renewable energy sources generate energy only in the first half of the simulation time (from 0 to 435 time units). Fig. 3.4.4 plots the amount of gas consumption of the optimal

and baseline schemes when the energy generation rate, ρ , varies from 1 to 6 units of energy per time unit. We observe that in this scenario, for large ρ , the benefits of the optimal scheme in reducing gas consumption compared to the baseline scheme is even more dramatic. This is again because the baseline scheme does not use the batteries of the buses effectively, as shown in Fig. 3.4.5 that shows the battery level of the CES over time for $\rho = 6$ and $\lambda = 0.1$. The energy level of the CES becomes zero shortly after the renewable energy generation stops, and hence the buses that start in the second half of the simulation time cannot obtain any energy from the CES. In the optimal scheme, the battery level of the CES is non-zero even when the renewable energy generation has stopped, allowing later buses to obtain energy and reduce gas consumption. Last, Fig. 3.4.6 plots the amount of gas consumption when the capacity of the CES increases from 10 to 100, when $\rho = 6$ and $\lambda = 0.1$. Compared to Fig. 3.4.6 (where renewable energy is generated throughout the simulation), we see the optimal scheme outperforms the baseline scheme more significantly, particularly when the capacity of the CES is small. This demonstrates that optimal scheduling of energy delivery is even more important for intermittent energy generation and CES with a relatively small capacity.

3.5 Related Work

The study closest to ours is [12], which determines the optimal energy transfer via PHEVs assuming a number of charge stations each with its own energy storage. Our study differs from [12] in that we assume only a single centralized energy storage. In addition, we also address several practical issues including energy loss during energy

exchanges, limited energy storage, and dynamic bus schedules. The study in [98] develops a hypergraph based approach to reduce the sum of all route hops from renewable energy sources to charge stations, which differs in scope from our study. Several studies are on scheduling the charging of PHEVs [46], [60]. These studies focus on when to charge a PHEV from the power grid, while our study focuses on renewable energy transfer by developing an optimal solution that determines how much energy a PHEV should charge or discharge at each charging point. ‘

Chapter 4

Network Coding based Transmission Schemes in DTNs with Group Meetings

4.1 Introduction

Many mobile wireless networks are Delay/Disruption Tolerant Networks (DTNs) where there is no contemporaneous path from a source node to a destination node. Examples include wireless sensor networks for wildlife tracking [32, 48], underwater sensor networks [61, 70], networks for remote areas or for rural areas in developing countries [2], vehicular networks [19, 40] and Pocket-Switched Networks [39]. Due to lack of contemporaneous path, data packets in DTNs are transmitted in a “store-carry-forward” manner [82]: a node receiving a packet buffers and carries the packet as it moves, passing the packet on to new nodes that it encounters. The packet is eventually delivered to the destination when the destination meets a node carrying

the packet.

In addition to lack of contemporaneous path, DTNs often have severe bandwidth limitation and power constraints. To address these challenges, a plethora of routing algorithms have been proposed for DTNs (e.g., [16, 32, 76, 77, 82]). Most studies assume pair-wise node encountering where nodes only meet in pairs. That is, when two nodes meet, no other nodes are in the neighborhood. While this assumption might be true for very sparse networks, in many DTNs, nodes can meet in groups where there can be more than two nodes and sometimes much more than two nodes. For instance, in wildlife tracking, a group of animals might meet together at a water hole; in underwater sensor networks, a group of nodes may be in the neighborhood of each other due to water currents; in Pocket-Switched Networks, a group of people may cluster at the same location, e.g., when attending a conference. In this study, we study how to effectively transmit a set of packets from a source to a destination in group meeting scenarios. The main problem we address is how to schedule packet transmission among a group of nodes that meet each other and have only a limited transmission bandwidth, in order to minimize the end-to-end delivery delay of packets while limiting the total number of transmissions in the network.

Network coding [10] can facilitate *distributed* and *localized* routing strategies, where nodes make independent decisions relying on knowledge about the local neighborhood [31]. These strategies are particularly attractive for DTNs due to rapidly changing topology, intermittent connectivity and limited bandwidth in the network. Network coding has been used for DTNs with pair-wise node encountering patterns [57, 99, 100]. In this dissertation, we apply network coding in group meeting scenarios. Our main contributions are as follows.

- We propose an algorithm to calculate the minimum time to deliver a group of packets, given a prior knowledge of all future meetings. This provides a lower bound for us to quantify the effectiveness of heuristic schemes.
- We develop two network coding based heuristic schemes for group meetings: one scheme based on the coefficient matrices of the coded packets buffered at the nodes, the other simply based on the ranks of the coefficient matrices. Both schemes are distributed, localized, and easy to implement. Both schemes use a token based technique to limit the total number of transmissions.
- Simulation results demonstrate that the two heuristic schemes achieve delays close to the minimum latency for moderate number of tokens. The rank-based scheme requires slightly larger number of transmissions than the matrix-based scheme, while incurring much lower signaling and computation overhead. Therefore, the rank-based scheme may be a preferred choice especially for networks with limited bandwidth and computation capabilities.

The remainder of Chapter 4 is structured as follows. In Section 4.2, we introduce the network model and performance metrics considered in this chapter. Section 4.3 presents the algorithm that obtains the minimum time to deliver a group of packets. Section 4.4 presents the two network coding based heuristic schemes. Section 4.5 describes performance evaluation. Section 4.6 reviews related work.

4.2 Background

In this section, we present the network model, traffic setting and performance metrics studied in this chapter. Table 4.2.1 summarizes the key notations for easy

Notation	Meaning
N	number of nodes in the network
\mathcal{V}	the set of nodes
\mathcal{L}	DTN meeting trace
K	generation size
b	#. of packets that can be exchanged during a meeting
$\mathcal{B}(u)$	#. of relay packets node u can store
\mathbb{F}_q	finite field, $q = p^n$ p is a prime, n is a positive integer.
D	group delivery delay
C	number of tokens

TABLE 4.2.1: Table of notations for Group Network Contact Problem

reference.

4.2.1 Network Model

We consider a network consisting of a set of N mobile nodes, denoted as \mathcal{V} , moving independently in a closed area. Each node is equipped with a wireless radio with a common transmission range so that when two or more nodes come within transmission range of each other (i.e., they *meet*), they can exchange packets. We refer to the list of meetings, sorted in temporal order, within a DTN during a certain time interval as a *DTN meeting trace*, denoted as $\mathcal{L} = l_1, l_2, l_3, \dots$, where each meeting, l_i , is a tuple (t_i, G_i, b_i) with t_i denote the time of the meeting, $G_i \subseteq \mathcal{V}$ denote the set of nodes that come into contact with each other during this meeting, and b_i denote the total number of packets that can be transmitted during the meeting. Due to the broadcast nature of wireless medium, we assume the packet transmitted by any node $u \in G_i$ will be received by all other nodes in G_i . During each meeting, transmission scheduling decides the allocation of bandwidth to the nodes in the group G_i , and the

transmission order, in order to optimize performance.

As for the buffer constraint, we assume each node can store an unlimited number of packets originated by itself or destined for itself, but can only carry a limited number of packets for other nodes. We represent the buffer constraint as a function, $\mathcal{B} : \mathcal{V} \rightarrow \mathbb{N}$ where $\mathcal{B}(u)$ is the number of relay packets that node u can carry.

4.2.2 Traffic Setting and Performance Metrics

We focus on unicast applications where each packet (generated by its source node) is destined to a single destination node. We suppose that each message generated by the application is segmented into a group of packets in order to take advantage of the short meetings. We denote the group of packets belonging to a message as $P_i, i = 1, 2, \dots, K$, and the delivery delay of packet P_i as D_i for $i = 1, 2, \dots, K$. The *group delivery delay*, D , is the time from the generation of the message, i.e., the group of packets, to the delivery of the entire group to the destination, and we have $D = \max_{1 \leq i \leq K} D_i$. In the following, we refer to group delivery delay simply as delivery delay. Another performance metric is the total number of transmissions in the network before the destination receives the message. We assume that once the destination receives the message, *recovery mechanisms* such as those in [32, 95] are used to remove the obsolete copies of the packets from the network to save resources. The third metric is the signaling overhead, i.e., the total amount of signaling data that a group of nodes use to exchange information so as to determine the transmission scheduling.

4.3 Minimum Delivery Delay

In this section, we present an algorithm to calculate the minimum delivery delay under a meeting trace and buffer constraint.

We use the 4-tuple (s, d, t_0, K) to denote a group of K unicast packets generated by source node s at time t_0 , all of which are destined for the same destination d . For (s, d, t_0, K) that can be delivered to the destination under the meeting trace \mathcal{L} and buffer constraints $\mathcal{B}(\cdot)$, there is a minimum delivery time by which all the K packets can be delivered to the destination. This time is in general achievable only by a centralized oracle with knowledge of all future meetings. The minimum delivery time clearly lower bounds the delivery time achievable by any routing scheme, and therefore is an ideal benchmark to compare different routing schemes with.

We first consider the related problem of determining the maximum number of unicast packets (generated at s at t_0 to be delivered to destination node d) that can be delivered under a given meeting trace \mathcal{L} and buffer constraint $\mathcal{B}(\cdot)$. Similar to related works [34, 100], we first build an *event-driven graph* $\mathcal{G}(\mathcal{L}, \mathcal{B}, (s, d, t_0, K))$ as follows, and then solve a maximum flow problem on \mathcal{G} . For ease of explanation, let $T = |\mathcal{L}|$, i.e., the number of meetings in the trace, and let t_1, t_2, \dots, t_T represent the times when meetings l_1, l_2, \dots, l_T occur.

1. For each node $u \in \mathcal{V}$, we introduce $T + 1$ nodes in \mathcal{G} , u_0, u_1, \dots, u_T , to represent the snapshot of node u at $t_0, t_1, t_2, \dots, t_T$ respectively.
2. We connect each snapshot of a node u_i to its next snapshot u_{i+1} with an **intra-node edge** (u_i, u_{i+1}) , and set its capacity as follows $c(u_i, u_{i+1}) = \mathcal{B}(u)$, denoting that node u can buffer packets until a later time instance¹.

¹If nodes have unlimited buffer, we can set the capacity for all intra-node edges to K (the total

3. For each meeting $l_i = (t_i, G_i, b_i)$ in \mathcal{L} , where nodes in set $G_i \subseteq \mathcal{V}$ come into contact with each other at time t_i , and up to b_i packets can be exchanged in a broadcast fashion, we introduce **inter-node edges** to connect nodes in G_i so that every node (at time t_i) is connected to every other node (at time t_{i+1}). For example, if $G_i = \{u, v, w\}$, we add the following edges into \mathcal{G} $(u_i, v_{i+1}), (u_i, w_{i+1}), (v_t, u_{i+1}), (v_t, w_{i+1}), (w_t, u_{i+1}), (w_t, v_{i+1})$, and assign capacity b_i to each of them.
4. For source node $s \in \mathcal{V}$, we add a super source node s to \mathcal{G} , and connect it to s_0 (source node at t_0) with an intra-node edge with capacity K , i.e., $c(s, s_0) = K$.
5. For destination $d \in \mathcal{V}$, we add a super sink node d to \mathcal{G} , and connect each node d_0, d_1, \dots, d_T to d with an intra-node edge of capacity K , i.e., $c(d_i, d) = K$, for $i = 0, 1, \dots, T$.

We use a network of 4 nodes in Fig. 4.3.1 to illustrate the construction of graph \mathcal{G} . We assume that the nodes are moving in an area divided into 2×2 grids, and all nodes in the same grid can communicate with each other. The lower figure represents the topology of the network at three consecutive time slots. The upper figure shows the constructed event-driven graph, when the source is a and the destination is node d . The intra-node edges are drawn in solid lines. The inter-node edges are drawn in dashed lines.

Let $f(\cdot)$ denote a flow from node s to node d in graph \mathcal{G} . The maximum number of packets (generated by node s and destined for node d) that can be delivered under meeting trace \mathcal{L} is the same as the maximum value of flow, $|f| = f(is, s_0)$ (Theorem 4 in [34]). We want to maximize the value of flow $|f|$, subject to constraints described

number of packets to be delivered from s to d).

below:

$$\underset{f}{\text{maximize}} \quad |f| = f(s, s_0) = \sum_u f(u, d)$$

subject to:

$$(1) \quad f(u_i, u_{i+1}) \leq c(u_i, u_{i+1}),$$

for each intra-node edge (u_i, u_{i+1})

$$(2) \quad f(u_i, v_{i+1}) \leq c(u_i, v_{i+1}),$$

for each inter-node edge (u_i, v_{i+1})

$$(3) \quad \sum_v f(u, v) = \sum_v f(v, u), \text{ for each node } u \neq s, u \neq d$$

$$(4) \quad \sum_{u \in G_i} \sum_{v \in G_i, v \neq u} f(u, v_{i+1}) \leq b_i,$$

for each meeting $l_i = (t_i, G_i, b_i)$ in \mathcal{L}

Constraints (1) and (2) are the capacity constraints for intra-node edges and inter-node edges respectively. Constraints (3) specify the flow conservation property for all nodes other than the source and destination of the flow, s, d . Note that a flow of value $|f|$ in \mathcal{G} corresponds to a set of end-to-end paths for delivering $|f|$ packets from s to d . As we are considering the minimum delay for a group of *unicast* packets, we only need to consider those end-to-end paths that deliver those packets first, and therefore we do not need to take into consideration that when a node in a group transmits, all nodes in the group receives the packet, and hence the flow conservation property. Lastly, constraints (4) specify that for a group meeting $l_i = (t_i, G_i, b_i)$, the total flows from nodes in the group G_i at time t_i to other nodes in the group at time t_{i+1} are bounded by b_i , the total bandwidth of the meeting².

²As $f(\cdot)$ is a non-negative mapping, capacity constraints on inter-node edges, i.e., constraints (2), are redundant as they are implied by constraints (4).

Again, we use the example in Fig 4.3.1 to illustrate the correspondance between the maximum flow in the event-driven graph and a transmission schedule in the DTN. Suppose only one packet can be exchanged during each meeting (i.e., $b = 1$). The maximum flow from the super source to super sink is 2, achieved by path $(source, a_0, a_1, a_2, d_3, sink)$ and path $(source, a_0, b_1, d_2, sink)$. The corresponding transmission schedule in DTN is: node a transmits the first packet in time 0 (nodes b, c receive the packet), node b then transmits the packet to destination d at time 1, and finally, node a transmits the second packet to destination d at time 2.

The above maximization problem is an integer linear programming problem, and can be solved using standard tools (e.g., CVX [66]). Since the constraints are integral, the solution is also integral.

The above formulation allows us to calculate the maximum number of packets that can be delivered under a given meeting trace \mathcal{L} , which we denoted as $MaxPacketDelivered(\mathcal{L})$. Now, in order to calculate the minimum delivery time to deliver a group of K packets, we only need to find the shortest prefix of the meeting trace under which K packets can be delivered. A simple way to do this is to start with a short prefix \mathcal{L}_1 of the meeting trace, If $MaxPacketdelivered(\mathcal{L}_1)$ is greater than or equal to K , we know the the minimum delivery time lies within the range $(0, t(\mathcal{L}_1)]$ (here we use $t(\mathcal{L})$ to denote the time of the last meeting in the meeting trace \mathcal{L}). If $MaxPacketdelivered(\mathcal{L}_1)$ is smaller than K , we consider a longer prefix \mathcal{L}_2 of the meeting trace (e.g., by doubling the length of the prefix) to see whether K packets can be delivered, and repeat this procedure until we find a prefix \mathcal{L}_n under which K packets can be delivered. In this case, we bound the minimum delivery time with range $(t(\mathcal{L}_0), t(\mathcal{L}_n)]$. To find the minimum delivery delay, we then perform a binary search in the above range to find the shortest prefix under which K packets

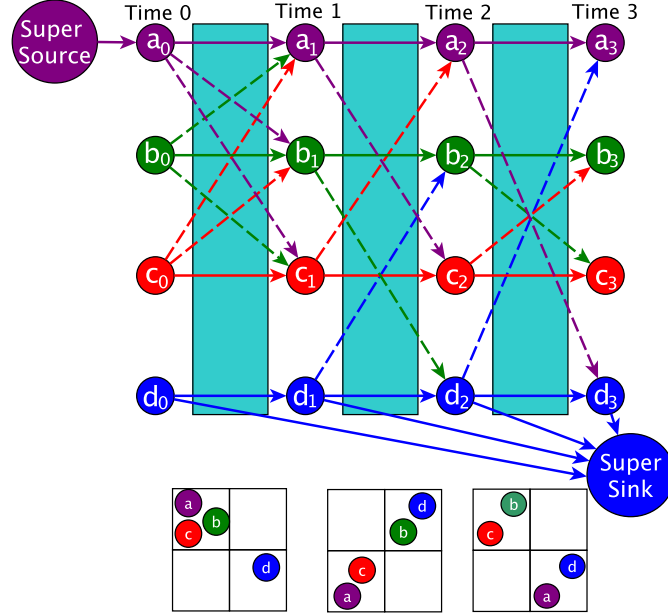


FIGURE 4.3.1: Illustration of the formulation to obtain the minimum delivery delay.

can be delivered.

4.4 Network coding based heuristic schemes

In this section, we present two network coding based heuristic schemes for group meeting scenarios. The reason for using network coding is motivated by its significant benefits for DTN routing for pair-wise scenarios [57, 99, 100]. Specifically, our proposed schemes use Random Linear Coding (RLC) [36], a special form of network coding. In the following, we first describe the basic idea of using RLC for DTN routing, and then present our schemes.

4.4.1 RLC based Routing Schemes

We assume that all packets have the same payload size equal to S bits. When RLC is used in packet data networks, the payload of each packet can be viewed as a vector of $\eta = \lceil S / \log_2(q) \rceil$ symbols from a finite field [55], \mathbb{F}_q of size q .

A collection of packets that may be linearly coded together by network nodes is called a *generation*. For example, the K packets that make up an application message can constitute a generation. We denote by $\mathbf{m}_i \in \mathbb{F}_q^\eta$, the symbol vector corresponding to packet P_i . A linear combination of the K packets is:

$$\mathbf{x} = \sum_{i=1}^K \alpha_i \mathbf{m}_i, \quad \alpha_i \in \mathbb{F}_q,$$

where addition and multiplication are over \mathbb{F}_q . The vector of coefficients, $\alpha = (\alpha_1, \dots, \alpha_K)$ is called the *encoding vector*, and the resulting linear combination, \mathbf{x} , is called an *encoded packet*. We say that two or more encoded packets are linearly independent if their encoding vectors are linearly independent. Each original packet, $\mathbf{m}_i, i = 1, 2, \dots, K$, can be viewed as a special combination with coefficients $\alpha_i = 1$, and $\alpha_j = 0, \forall j \neq i$.

Under RLC schemes, network nodes store and forward encoded packets, together with their encoding vectors. If the set of encoded packets carried by a node contains at most r linearly independent encoded packets $\mathbf{x}_1, \dots, \mathbf{x}_r$, we say that the rank of the node is r . We refer to the $r \times K$ matrix (denoted as \mathbf{A}) formed by the encoding vectors of $\mathbf{x}_1, \dots, \mathbf{x}_r$ as the node's *encoding matrix*. Essentially, the node stores r independent linear equations with the K original packets as the unknown variables, i.e., $\mathbf{A}\mathbf{M} = \mathbf{X}$, where $\mathbf{M} = (\mathbf{m}_1, \mathbf{m}_2, \dots, \mathbf{m}_K)^\top$ is a $K \times \eta$ matrix of the K original packets, and $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r)^\top$ is an $r \times \eta$ matrix of the r encoded packets. When a

node (e.g., the destination) reaches rank K (i.e., *full rank*), it can decode the original K packets through matrix inversion, solving $\mathbf{A}\mathbf{M} = \mathbf{X}$ for $\mathbf{M} = \mathbf{A}^{-1}\mathbf{X}$ using standard Gaussian elimination algorithm.

We illustrate data forwarding under RLC schemes using the transmission from node u to node v as an example. Node u generates a random linear combination (\mathbf{x}_{new}) of the combinations stored in its buffer $\mathbf{x}_1, \dots, \mathbf{x}_r$: $\mathbf{x}_{new} = \sum_{j=1}^r \beta_j \mathbf{x}_j$, where the coefficients β_1, \dots, β_r are chosen uniformly at random from \mathbb{F}_q . Clearly, \mathbf{x}_{new} is also a linear combination of the K original packets. This new combination, along with the coefficients *with respect to the original packets*, is forwarded to node v . If among $\mathbf{x}_1, \dots, \mathbf{x}_r$, there is at least one combination that cannot be linearly expressed by the combinations stored in node v , node u has useful (i.e., *innovative*) information for node v , and \mathbf{x}_{new} is useful to node v (i.e., increases the rank of node v) with probability greater than or equal to $1 - 1/q$ (*Lemma 2.1* in [23]). When v receives \mathbf{x}_{new} , it stores \mathbf{x}_{new} into its buffer if there is still space in its buffer; otherwise, one existing encoded packet in the buffer is replaced by its linear combination with \mathbf{x}_{new} .

4.4.2 RLC based Routing Schemes for Group Meeting Scenarios

When a group of $n \geq 2$ nodes meet and can only exchange b packets, the key decision is transmission scheduling, i.e., allocating the bandwidth to the nodes in the group, and determining the transmission order. Intuitively, nodes that have innovative packets for other nodes in the group should transmit first and use more bandwidth. In addition, to limit the energy consumption in delivering a generation of packets, the total number of transmissions that is allowed in the network should

be limited.

Several previous works in DTNs proposed schemes to limit the total number of transmissions. The binary spray-and-wait [57, 77] scheme assumes pair-wise meetings, and hence cannot be directly applied to group meeting scenarios. In our heuristics, we adopt the token-based RLC technique in [100] to limit the total number of transmissions in the network. Specifically, at the beginning, the source has C tokens; the rest of the nodes do not have any token. When a group of nodes meet, their tokens are aggregated together, used jointly and then distributed among the nodes at the end of the encountering. We will show that the total number of transmissions in the network is no more than $C + K$ with high probability.

Next, we present two transmission scheduling schemes for group meeting scenarios to be used with RLC based scheme as described in Section 4.4.1. In the matrix based scheme, nodes determine transmission scheduling based on their encoding matrices; in the rank based scheme, nodes determine transmission scheduling based on the ranks of their encoding matrices.

For ease of exposition, we assume that a group of n nodes, denoted as v_1, \dots, v_n meet and can transmit up to b packets during the group meeting. For each node v_i , we denote its encoding matrix as \mathbf{A}_i , its rank as r_i , and its number of tokens as c_i . We define the number of innovative packets that v_i has *relative to* node v_j , denoted as r_{ij} , to be the rank of the matrix formed by \mathbf{A}_i and \mathbf{A}_j (i.e., the rank of v_j when it gets all the coefficient combinations from v_i) subtracted by the rank of v_j .

Matrix based Scheme

In the matrix based scheme, when the group of nodes meet, each node in the group, v_i , broadcasts its encoding matrix \mathbf{A}_i and token number c_i to the rest of the nodes in the group. After receiving the encoding matrices from other nodes, each node v_i calculates *i*). the rank of the encoding matrix of node v_j , denoted as r_j , $j = 1, \dots, n$, *ii*). the number of innovative packets it has relative to node v_j , i.e., r_{ij} , $j = 1, \dots, n$, and *iii*). the total number of tokens for the group, $c = \sum_{i=1}^n c_i$.

When the bandwidth is b and the total number of tokens in the group is c , there can be at most $\min(b, c)$ rounds of packet transmissions (in a round, one node generates and transmits a new packet which is a linear combination of the packets in its buffer as described in Section 4.4.1). Let b_g and c_g denote respectively the remaining bandwidth and the remaining number of group tokens. Initially $b_g = b$ and $c_g = c$. Each node maintains a copy of r_{ij} , r_i , $i, j = 1, \dots, n$, b_g and c_g .

We first consider the scenario where the destination node is not in the group, i.e., $v_i \neq d$, $i = 1, \dots, n$. In each round, node v_i can transmit only when all the following four conditions hold: $b_g > 0$, $c_g > 0$, v_i has at least one innovative packet for other nodes, i.e., $\sum_j r_{ij} > 0$, and v_i has the largest rank among all the nodes that have at least one innovative packet for other nodes.

After node v_i 's transmission, each node reduces its copy of b_g (the remaining bandwidth) and c_g (remaining token) by one. In addition, each receiving node v_j updates its copy of r_{ij} to $\max(0, r_{ij} - 1)$, $j = 1, \dots, n, j \neq i$. In other words, we assume that the number of innovative packets that v_i has relative to other nodes is reduced by one. We make this assumption since it happens with high probability (more specifically, the probability is greater than or equal to $1 - 1/q$ (*Lemma 2.1* in [23])).

There is no verification on whether this is indeed the case, because the verification requires additional signalling overhead and hence additional energy consumption. Last, each node v_j updates its copy of r_j to $\min(K, r_j + 1)$, for $j = 1, \dots, n$, and $j \neq i$, again because this happens with high probability.

The group of nodes repeat the above transmission until $b_g = 0$, or $c_g = 0$, or none of the nodes in the group has any innovative packet to send. When transmission ends, the remaining group tokens are distributed among the group of nodes proportional to the ranks of nodes.

For the case when the destination node is among the group of nodes that meet, we remove the restriction of the group tokens, and allow each non-destination node v_i to transmit combinations as long as there is bandwidth and it has innovative packets relative to destination d , i.e., $r_{id} > 0$. Since the number of independent packets is K , the number of transmissions in this case is bounded by K with high probability. And therefore the total number of transmissions in the network is no more than $C + K$ with high probability since the total number of transmissions made to non-destination nodes is bounded by C , and the number of transmissions to destination is bounded by K with high probability. The actual number of transmissions is smaller when a recovery scheme is used.

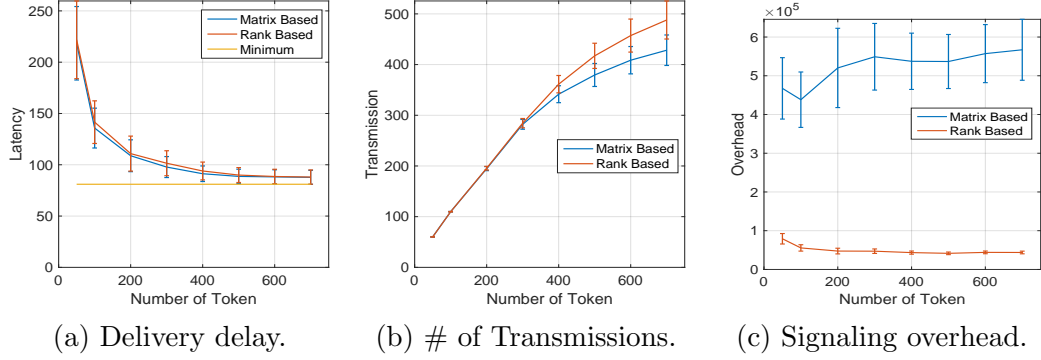
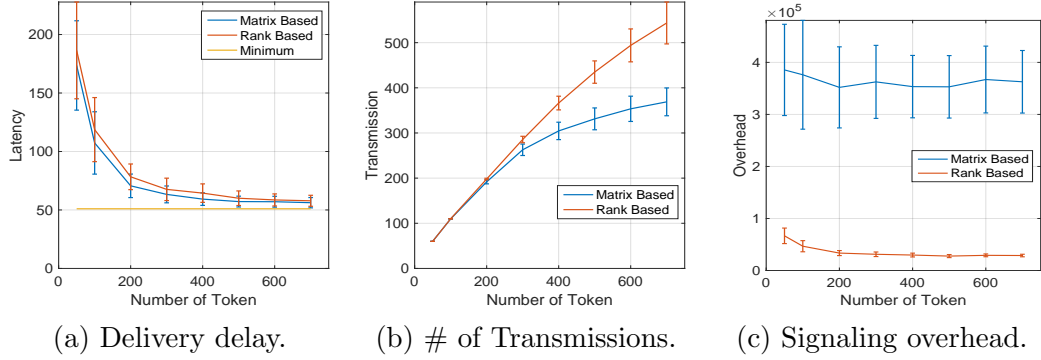
Rank based Scheme

The rank based scheme differs from the matrix based scheme in that a node broadcasts the rank of its encoding matrix, instead of the encoding matrix itself, at the begining of each meeting. More specifically, when the group of nodes meets, each node v_i broadcasts its rank r_i and token number c_i to all other nodes in the group.

Each node v_i stores and maintains a copy of r_j , $j = 1, \dots, n$. In each transmission round, node v_i can transmit only when all the following four conditions hold: $b_g > 0$, $c_g > 0$, v_i has the highest rank, i.e., $r_i > 0$ and $r_i \geq r_j$ (when multiple nodes have the highest rank, we break the tie randomly), and there still exists at least a node with rank below K .

After v_i 's transmission, each node reduces its copies of b_g and c_g by one, and updates $r_j = \min(K, r_j + 1)$, for $j = 1, \dots, n, j \neq i$. For similar reason as described for the matrix based scheme, the total number of transmissions in the network for the rank based scheme is no more than $C + K$ with high probability.

The rank based scheme incurs less signaling overhead than the matrix based scheme. Specifically, for the matrix based scheme, the signaling overhead for a group of n nodes is $\sum_{i=1}^n \text{size}(\mathbf{A}_i) \log_2 q + n \log_2 C$ bits. The first term is the signaling overhead for transmitting the encoding matrices, where $\text{size}(\mathbf{A}_i)$ represents the number of elements in \mathbf{A}_i and each element has $\log_2 q$ bits. The second term is the signaling overhead for transmitting the number of tokens (since C is the maximum number of tokens at a node). For the rank based scheme, the signaling overhead is $n \lceil \log_2 K \rceil + n \log_2 C$ since the signaling overhead for transmitting the ranks is $n \lceil \log_2 K \rceil$ (a rank is no more than K). In our simulation setting, since $K = 10$, $q = 2^8$, and $\sum_{i=1}^n \text{size}(\mathbf{A}_i)$ can be significantly larger than n , the signaling overhead for each meeting under the rank based scheme can be much lower than that under the matrix based scheme. On the other hand, in the matrix based scheme, each node has an accurate estimate of the number of innovative packets that it has relative to other nodes, which may lead to better decisions, and hence shorter delivery delay and less transmissions. We compare the performance of these two schemes in Section 4.5.

FIGURE 4.5.1: Performance of the matrix and rank based schemes when $b = 1$.FIGURE 4.5.2: Performance of the matrix and rank based schemes when $b = 3$.

4.5 Performance Evaluation

We evaluate the performance of the matrix and rank based schemes using simulation. In the following, we first present the results in the basic setting with a relatively small number of nodes and sufficient buffer size. We then investigate the impact of node density and buffer size on the performance. At the end, we compare the performance of our group meeting based schemes with pairwise schemes, and present energy consumption.

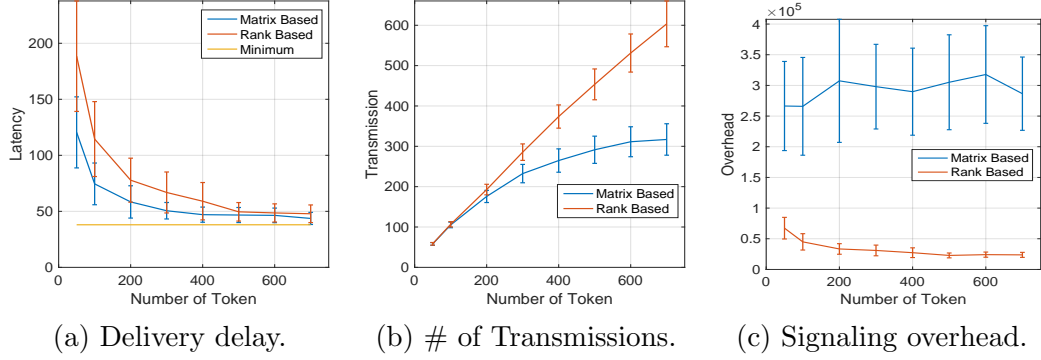


FIGURE 4.5.3: Performance of the matrix and rank based schemes when $b = 9$.

4.5.1 Basic Setting

We simulate a grid network of 15×15 grids. There are 101 nodes in the network. Among them, 100 nodes are mobile, and one node is static. The mobile nodes are initially uniformly distributed in the network. They move in time slots. In each time slot, a node moves in one of the four directions, left, right, up or down, into the adjacent grid. If following the direction does not lead to a valid adjacent grid (i.e., if a node is in the top left grid, then moving left or up does not lead to a valid adjacent grid), then the node stays in the current grid. One of the mobile nodes is randomly chosen as the source. The source generates a generation of $K = 10$ packets and encodes them using RLC at the beginning of a simulation run. The single static node, located at the center of the network, acts as the destination.

We assume nodes in the same grid can transmit to each other. In addition, due to the broadcast nature of wireless transmission, when one node transmits, the rest of the nodes in the grid can receive the packet. We assume each node has sufficient amount of buffer space (specifically the buffer can hold 200 packets). For a group of nodes in the same grid, the transmission bandwidth b is set to allow 1, 3, or 9 packet transmissions during an encountering. The number of tokens allowed to transmit a

generation of packets, C , is set to 50, 100, 200, 300, 400, \dots , 700. For each simulation setting, we use the algorithm in Section 4.3 to obtain the minimum delivery delay. For the matrix and rank based schemes, we obtain the delivery delay, the total number of transmissions that is needed before the destination recovers the original packets, and the total amount of signaling overhead. For each setting, we generate 30 meeting graphs using random seeds, and obtain the average results and the standard deviation.

We first present the results when the transmission bandwidth, $b = 1$. Fig. 4.5.1 plots the performance of the matrix and rank based schemes. Specifically, Fig. 4.5.1(a) plots the delivery delay versus the number of tokens; the minimum delivery delay is also plotted in the figure (which is independent of the number of tokens and hence is a horizontal line). We observe that the performance of the matrix and rank based schemes is similar. This is because, when $b = 1$, only a single node can transmit a single packet when a group of nodes meet; the node with the most innovative packets (in the matrix based scheme) is likely to coincide with the node with the highest rank (in the rank based scheme). For both the matrix and rank based schemes, the delivery delay decreases when the number of tokens, C , increases. This is expected since a larger number of tokens allows more transmissions in the network and more opportunities for nodes to exchange information. In addition, there is a diminishing gain in increasing the number of tokens: the decrease in delivery delay is significant at the beginning and then becomes less significant afterwards. For instance, under the matrix based scheme, the delivery delay for $C = 400$ is similar to that when $C = 700$, respectively 18.5% and 13.9% larger than the minimum latency.

Fig. 4.5.1(b) plots the number of transmissions when $b = 1$. The results for both the matrix and rank based schemes are plotted in the figure. These two schemes achieve similar performance for relatively small C . For relatively large C , the number

of transmissions under the matrix based scheme is noticeably lower. This might be because under the matrix based scheme, a node knows accurately whether it has innovative packets for other nodes or not, and may not transmit packets even if there are tokens allowing it to transmit. For the rank based scheme, as long as there are tokens and available bandwidth, a node will transmit unless its rank is K and the ranks of all the other nodes are K . Fig. 4.5.1(c) plots the signaling overhead when $b = 1$. As explained in Section 4.4.2, the matrix based scheme leads to significantly higher overhead.

We next compare the total communication overhead, i.e., the sum of the overhead for transmitting data packets and the signaling overhead, of the two schemes. Assume each data packet is 1500 bytes (i.e., the Maximum Transfer Unit in a typical network). When $C = 400$, from Fig. 4.5.1(b), the average numbers of transmissions under the rank and matrix based schemes are 361.6 and 341.3 respectively, and hence the overhead for transmitting data packets under the rank based scheme is $1500 \times 8 \times (361.6 - 341.3) = 2.4 \times 10^5$ bits more than that of the matrix based scheme. On the other hand, from Fig. 4.5.1(c), the signal overheads of the rank and matrix based schemes are 4.3×10^4 bits and 5.4×10^5 bits respectively, and hence the signaling overhead of the rank based scheme is $(5.4 - 0.43) \times 10^5 = 5.0 \times 10^5$ bits lower than that of the matrix based scheme. Overall, the total communication overhead of the rank based scheme is $(5.0 - 2.4) \times 10^5 = 2.6 \times 10^5$ bits lower than that of the matrix based scheme. On the other hand, the delivery delay under the rank based scheme is 2.8% larger than that of the matrix based scheme (93.9 versus 91.3, see Fig. 4.5.1(a)).

We now present the results when the transmission bandwidth, b , is larger. Fig. 4.5.2 plots the results when $b = 3$. We observe similar trends as those when $b = 1$. The delivery delay under these two schemes is still similar for the various values of C ,

although the difference between the two schemes is more noticeable than that when $b = 1$. For the number of transmissions, the performance under these two schemes is similar for small C , while for large C , the difference is more significant than that when $b = 1$. For the signaling overhead, the rank based scheme is still significantly lower than that of the matrix based scheme. In general, we observe similar tradeoff as that when $b = 1$. For instance, when $C = 300$, the delivery delay under the rank based scheme is 6.8% larger than that of the matrix based scheme (67.6 versus 63.3), while the total communication overhead (i.e., considering both data transmission and signaling; assuming each data packet is 1500 bytes) is 8.0×10^3 bits lower.

Fig. 4.5.3 plots the results when $b = 9$. While the overall trends are similar to those when $b = 1$ and $b = 3$, the delivery delay under the matrix based scheme is significantly lower than that of the rank based scheme when C is below 400, indicating that when b is large, using encoding matrices to determine the transmission scheduling achieves more benefits than simply using rank information. In addition, Fig. 4.5.3(b) shows that the number of transmissions under the matrix based scheme increases much more slowly than that under the rank based scheme. As a result, the rank based scheme can lead to more total communication overhead than the matrix based scheme. For instance, when $C = 300$, again assuming each data packet is 1500 bytes, the overhead of data transmission under the rank based scheme is 6.3×10^5 bits more than that of the matrix based scheme, outweighing its savings in signaling overhead (which is 2.7×10^5 bits less than that of the matrix based scheme).

Summarizing the above, we observe that both the matrix and rank based schemes achieve delivery delay similar to the minimum delivery delay for moderate number of tokens (when $C = 300$ or 400). These two schemes present different tradeoffs in the delivery latency and communication overhead. In general, when b is small, the rank

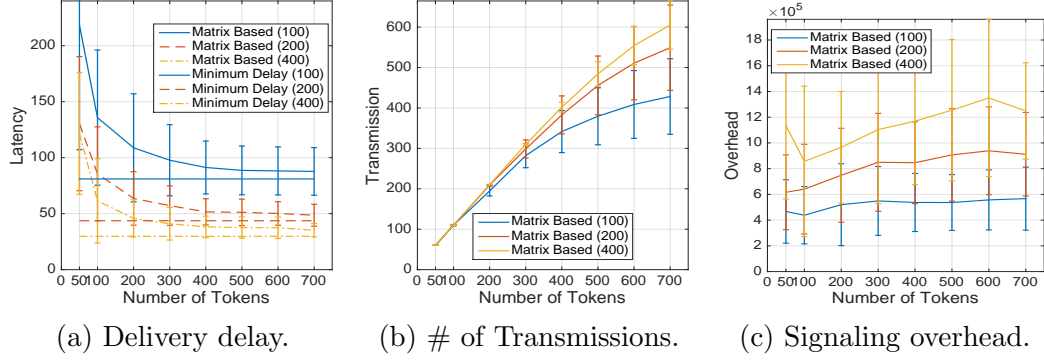


FIGURE 4.5.4: Impact of node density: performance of the matrix based scheme, $b = 1$.

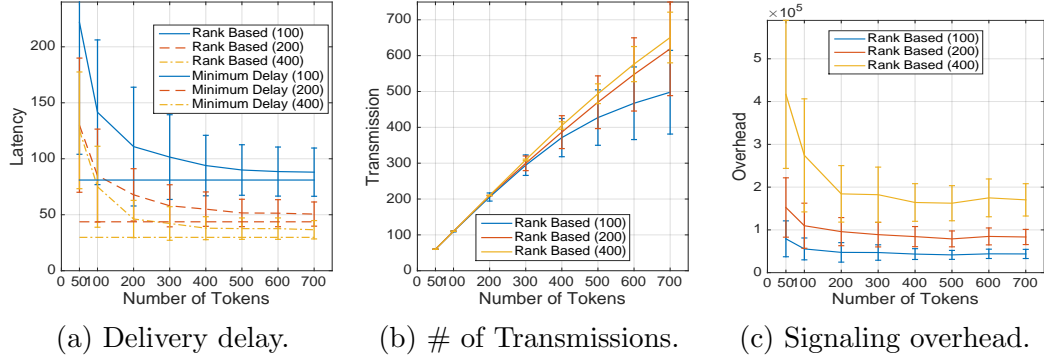


FIGURE 4.5.5: Impact of node density: performance of the rank based scheme, $b = 1$.

based scheme seems to be more preferable; while when b is very large, the matrix based scheme seems to be more preferable. Both schemes are easy to implement and only incur signaling at the beginning of the group encountering. For large b , the number of transmissions under the rank based scheme can be reduced by adding feedback, i.e., after a node transmits a packet, the rest of the nodes provide feedback on whether their ranks are indeed increased. The additional feedback, however, adds more complexity to the scheme.

4.5.2 Impact of Node Density

We now investigate the impact of node density on the performance of our schemes. Fig. 4.5.4(a) plots the delivery delay of the matrix based scheme when the number of mobile nodes is varied from 100, 200 to 400. The minimum delivery delay under each node density is also plotted in the figure. We observe the delivery delay decreases when increasing node density. This is because the average number of nodes in a group increases with node density, and hence more nodes can receive a packet when it is being transmitted, accelerating packet dissemination in the network. For instance, when $C = 400$, the delivery delay reduces by 40.8% when the number of nodes increases from 100 to 200; when the number of nodes further increases from 100 to 400, the delivery delay reduces by 59.1%. On the other hand, there is a diminishing gain in increasing the number of nodes in reducing delivery delay. Fig. 4.5.4(b) and Fig. 4.5.4(c) plot the number of transmissions and the signaling overhead, respectively. As expected, both increase with the number of nodes in the network. Fig. 4.5.5 plots the results for the rank based scheme. We observe similar trends as those in the matrix based scheme.

4.5.3 Impact of Buffer Size

We now investigate the impact of buffer size on the performance of our schemes. Specifically, the buffer size is varied to the size of 2, 4, \dots , or 10 packets. Fig. 4.5.6(a) plots the delivery delay of the matrix and rank based schemes, $b = 1$, $C = 400$. The minimum delivery delay under each buffer size is also plotted in the figure. We observe that the delivery delay decreases dramatically initially when increasing the buffer size, and the decrease is less dramatic afterwards.

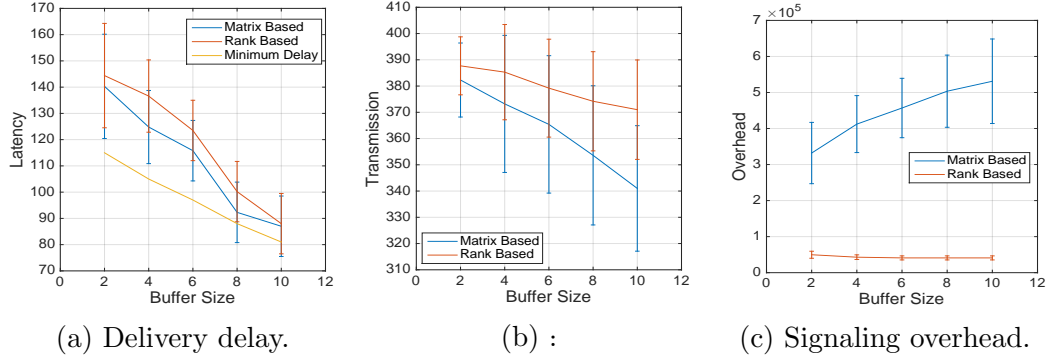


FIGURE 4.5.6: Impact of buffer size: performance of the matrix and rank based schemes with 100 mobile nodes, $b = 1$, $C = 400$.

Fig. 4.5.6(b) plots the number of transmissions. As expected, the number of transmission decreases when increasing the buffer size since more packets can be held in each node, leading to faster delivery to the destination. Fig. 4.5.6(c) plots the signaling overhead. For the rank based scheme, the signaling overhead decreases as the buffer size increases because less transmissions are needed for the destination to receive all the packets. For the matrix based scheme, while the number of transmissions is less under larger buffer sizes, the size of the encoding matrix also tends to be larger. Combining the two factors together, the signaling overhead under the matrix based scheme increases with the buffer size.

4.5.4 Comparison with Pairwise Schemes

We now compare the performance of our schemes with pairwise schemes. Specifically, in pairwise schemes, only a pair of nodes exchange packets with each other (even a group of nodes are in the neighborhood). In analogous to the two group based schemes, we consider two types of pairwise schemes, one is matrix based pairwise scheme and the other is rank based pairwise scheme. Fig. 4.5.7 plots the results

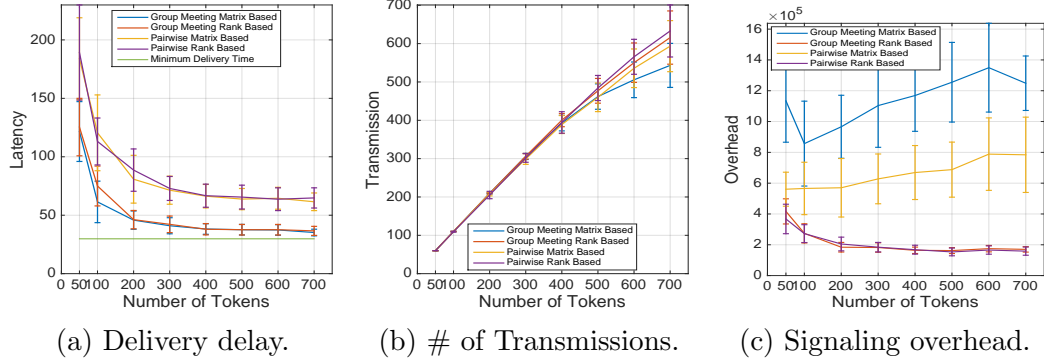


FIGURE 4.5.7: Performance comparison of group based schemes and pairwise schemes, $N = 400$, $b = 1$ and buffer size is unlimited.

when $N = 400$, $b = 1$ and the buffer size is unlimited. We see that the delivery delay under the group based schemes is much lower compared to pairwise schemes, since group based schemes take advantage of the groups to achieve faster packet dissemination, while pairwise schemes only consider two nodes each time. For relatively large number of tokens, the number of transmissions under the pairwise scheme is larger than its group based counterpart since it takes longer and more transmissions for the destination to receive all the packets. The signaling overhead under the pairwise schemes is lower, as expected.

4.5.5 Energy Consumption

Many studies have analyzed energy requirement in wireless networks [25, 28, 35, 72, 86, 88]. In the following, we use a simple energy consumption model from [35]. Specifically, let $E_T(k, d)$ denote the energy for transmitting a k -bit message for a distance of d . Let $E_R(k)$ denote the energy for receiving a k -bit message. Assume the radio dissipates $E_{elec} = 50$ nJ/bit to run the transmitter or receiver circuitry and $\epsilon_{amp} = 100$ pJ/bit/m² for the transmit amplifier to achieve an acceptable signal noise

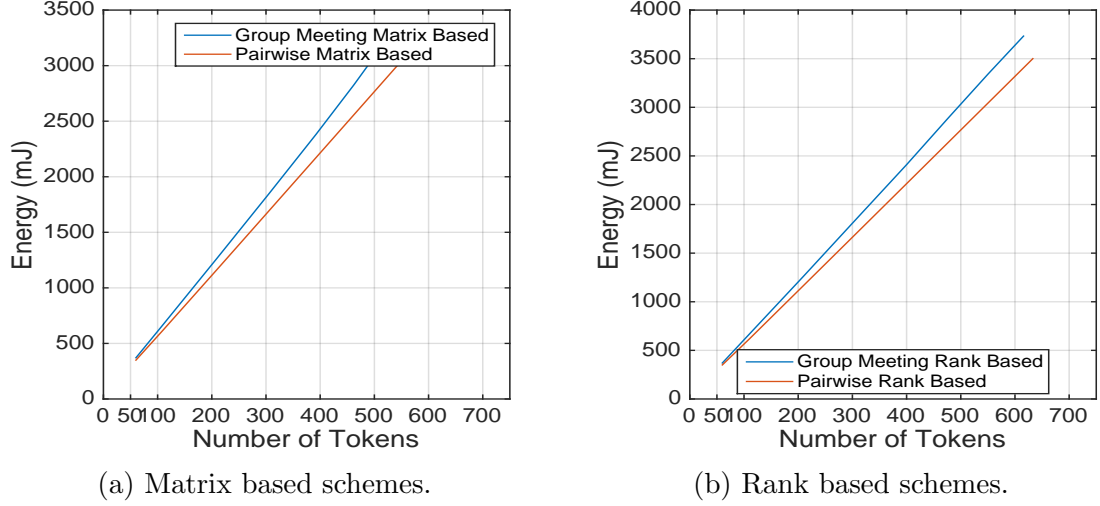


FIGURE 4.5.8: Energy consumption of pairwise and group based schemes, $N = 400$, $b = 1$ and buffer size is unlimited.

ratio. Then we have

$$E_T(k, d) = E_{elec} \times k + \epsilon_{amp} \times k \times d^2$$

$$E_R(k) = E_{elec} \times k$$

Let $E_{idle} = 100$ nJ/s denote the idle energy (i.e., when a node is not receiving or transmitting packets). Let N_T and N_R denote respectively the number of packets that are transmitted and received in the network. Let T_d denote the delivery latency. Then the total energy consumption in the network is (the energy consumption for signaling overhead is not counted since signaling packets are much smaller than data packets)

$$E = E_T(k, d) \times N_T + E_R(k) \times N_R + E_{idle} \times T_d$$

We assume $d = 60$ m, that is, the wireless radio on each node can transmit for

a distance of 60 meters. Furthermore, we assume each data packet is 1500 bytes. Fig. 4.5.8 plots the results. We observe that pairwise schemes have slightly lower energy consumption compared to group based schemes. On the other hand, they lead to much higher delivery latency, and hence overall they are inferior to group based schemes.

4.6 Related Work

Previous works have studied the application of network coding to broadcast and unicast applications in DTNs. For broadcast applications, Widmer *et al.* [92, 93] showed that a RLC routing scheme achieves higher packet delivery rates than the non-coding scheme with the same forwarding overhead. For unicast applications, Zhang *et al.* [99, 100] investigated the benefits of RLC through analysis and simulation, and proposed a token based scheme to limit the number of transmissions.

Lin *et al.* proposed and analyzed a different replication control scheme ([57]), and proposed Ordinary Differential Equation (ODE) models for estimating delivery delay and number of transmissions for RLC schemes and non-coding schemes ([56]). The above studies assumed pair-wise contacts. In this chapter, we also study RLC based schemes for unicast applications in DTNs, however, our work differs from the above works in that we consider group meeting scenarios, and focus on the resulting transmission scheduling problem under such group meeting.

Several studies [44, 89] are on the application of erasure coding to DTNs, where the source encodes a message into a large number of blocks, such that as long as a certain fraction or more of the coded blocks are received, the message can be decoded. For

DTNs where there is prior knowledge about paths and their loss behavior, Jain *et al.* [44] studied how to allocate the coded blocks to the multiple lossy paths, in order to maximize the message delivery probability. To reduce the variance of delivery delay in DTNs with unpredictable mobility, Wang *et al.* ([89]) proposed to encode each message into a large number of coded blocks which are then transmitted to a large number of relays helping to deliver the coded blocks to the destination. Our study differs from them in that we focus on network coding, and specifically RLC.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this dissertation, an optimal renewable energy transfer problem is studied by using two different solutions. In Chapter 2 the the solution is provided by a design which requires charge station network for a bus system. Specifically, a unique approach is to allow buses doing energy exchanges via charge stations. The problem is well defined and formulated. The solution of optimization problem is shown that it determines how much energy a bus should deposit or withdraw at a charge station so that the total amount renewable energy used by the bus system is maximized. Simulation results using the Manhattan city bus system demonstrates that the proposed approach provides an effective way for renewable energy to be transferred and shared in a bus system. One of the key point in the Chapter 2 is to determine the locations of the charge stations which has been already studied. Proposed linear programming has proven that it solves the optimal renewable energy transfer problem efficiently.

In Chapter 3, same problem is solved with a different architecture. The main idea is to place a central storage for PHEVs that considering replacement of charge stations in a public transportation system since having batteries in every charge station location may not be feasible. Most of the large cities have already underground system, so proposed centralized storage approach can be applied to those areas. Chapter 3 shows how to determine the optimal energy delivery schedules for PHEVs to minimize the amount of gas consumption when there is a single centralized energy storage that stores the energy generated by renewable energy sources. Again same problem is formulated with different constraints as an optimization problem and solved by using linear programming. Simulation results using the same data from Chapter 2 also shows that our approach significantly outperforms a baseline strategy. In addition, our approach uses the batteries of the PHEVs efficiently, and hence only a small battery at the central storage is sufficient to realize most of the gains.

In Chapter 4, a unique approach for delay tolerated networks is studied. The main objective is to reduce time delay while having reliable communication medium between wireless devices. Most of the previous studies have considered pair wise communication in closed area while communication range is sufficient. We develop a group based scheme which makes sure that all available bandwidth is used to improve the transmission of packets to the destination. The results of proposed matrix and rank based schemes proves that reliable connection with moderate delivery time and energy efficiency is possible. To allow more bandwidth, nodes are considered to communicate each other whenever they are in the communication range. In group meeting scheme, different scenarios can be studied. Especially, our group meetings approach has useful properties to study. Dynamic adaptation of buffer size could increase throughput while less nodes are around. Simulation results demonstrate that

both algorithms achieve delays close to the minimum latency for moderate number of tokens. They present different tradeoffs in the number of transmissions and the signaling overhead. As future work, we will explore how to determine the optimal number of tokens for these two schemes.

5.2 Future Works

In Chapter 2, placement of charge station strategy is used from [97]. There can be other alternatives which can advance improvements of gasoline usage potentially since most visited locations of buses while they are traveling can be found easily. When another placement strategy is found, it can be applied to the current work smoothly. Charge station placement strategy is a challenging question and has been studied previously [53, 96] Solving optimal energy consumption while considering different parameter for charge station strategy would even increase efficiency for energy exchanges. The loss factor while transmitting energy was also not considered since it could be negligible.

For the second work in electrical vehicle networks, vehicle to vehicle(V2V) technology can be a good direction to extend current implementation. Obviously, transmission of electricity through the vehicles by only using their batteries might not be possible every time. If there is a foundation for allowing vehicles to exchange peer 2 peer electrical energy directly, there will be no need for central storage nor charge station on the routes. Scheduling their energy exchange events and more aggressive control mechanism over energy transmission are also open questions. Since electricity is thought as data packets in the Chapter 3, many different data communication re-

lated solution can be applied in a transportation system. As future work, we plan to study vehicle to vehicle energy transfer by using only EV batteries, which can further reduce investment and operation costs.

For both Chapter 2 and Chapter 3 we assume that the central oracle can quickly response in any urgent situation since all the charging equipment for the buses are under control (they are wireless communication capable and controlled). Offline and online modes are introduced. Another interesting study could be the calculation of new energy exchange variables since the new situation would require changes in current time scheduling. Boundaries for energy exchange amounts can reduce the investment of abundance battery size thus can be more economical.

In Chapter 4, choosing optimum token number is also a challenging question to solve. While exchanging rank and matrix information, neighborhood discovery information could be added to the shared data in order to improve bandwidth allocations. Our simulations consider only unicast applications, studying multiple source and destination node could be very interesting and challenging. To compare our results, we introduce a naive pair wise method. It could be improved such a way that multiple nodes could also listen only while there is broadcasting data in the same communication.

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