Optimization of Electric Vehicle Charging Schedules Based on Individual Driving Habits and Real-World Scenarios

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Abstract

This study aims to address the issue of range anxiety in electric vehicle (EV) drivers by developing optimal charging schedules that are based on individual driving habits, proximity to charging facilities, and environmental factors. A scheduling approach was employed to match the usage profile of the EV with charging windows, with the objective of minimizing charging cost, time loss, and overall degradation of the EV. The development of a driving profile was undertaken for three scenarios: short commute, long commute, and senior citizen, and charging windows were defined to reflect real-world situations. With this, an optimization model was implemented using Python's pyworkforce package, with the constraint of charging rate per hour. The results provide tabulated quantitative values for optimal charging schedules on a weekly basis and can assist EV drivers in adapting to an EV lifestyle and reducing range anxiety. This research provides valuable insights into addressing the critical issue of range anxiety in EV adoption and has the potential to encourage more individuals to switch to EVs by alleviating their concerns regarding limited driving range.

Keywords
Electric Vehicle (EV), Charging, Optimization, Sustainable development, Energy.

1. Introduction
With the insurgence of climate change concerns, the use of electric vehicles (EVs) has become more prevalent in consumer trends. Although EVs provide a functional solution to the negative environmental impacts of standard fuel vehicles, they also pose additional problems in efficiency and convenience as users often experience range anxiety. This consumer behavior pattern can be characterized by the fear of running out of charge prior to reaching the destination or prior to reaching a nearby charging station, leaving the driver stranded (Guo et al. 2018). As EVs are a relatively new technology in the automotive industry, consumers may not be as intuitively acclimated to developing an optimal charging schedule in accordance with their driving habits, in comparison to the instinctive refueling schedule that gas-powered vehicle drivers are accustomed to; moreover, gas stations are typically more frequently located within urban settings, allowing for a reduction in range anxiety. Given this, EV drivers are more likely to experience high rates of range anxiety and exhibit remunerative behaviors as a response. For example, some drivers might charge their EVs excessively, leading to increased energy consumption and less charger availability for other drivers. As such, there is a need to quantify and model an optimal EV charging schedule in consideration of daily activity constraints and energy consumption minimization.

1.1 Objectives
To better acclimatize individuals to an EV lifestyle, optimal charging schedules can be created that consider varying driving habits, proximity to charging facilities, and the environment in which the individual drivers reside. By

focusing on the individual rather than society as a whole, the aforementioned schedules can be far more flexible in terms of the input parameters, constraints, and priorities of the individual.

The goal of this paper is to create tabulated quantitative values for optimal charging schedules on a weekly basis based on varying input parameters. These input parameters include driving habits (amount driven), season of the year, and opportunity cost of missed time. The objective function of the created models primarily focus on the minimization of cost to the individual from charging cost, loss of time, and overall degradation of EV.

2. Literature Review

2.1 Relevant Research

Optimal electric vehicle (EV) charging schedules are a topic of growing interest among researchers and policymakers seeking ways to reduce the impact of EVs on the electric grid and optimize the use of renewable energy sources. There are many factors that can affect the effectiveness of optimized charging schedules for electric vehicles. A recent study investigated the impact of various parameters on the effectiveness of optimized charging schedules (Zhang et al. 2019). The study used simulation models to analyze the impact of driving behavior, charging infrastructure, and the cost of electricity on the cost and emissions savings achieved by optimized charging schedules. The study found that optimized charging schedules can significantly reduce the cost and emissions of EV ownership by 15%, but their effectiveness depends on the availability of charging infrastructure, the behavior of EV drivers, and the cost of electricity. The study suggests that policymakers and EV owners should consider these factors when developing and implementing optimized charging schedules.

Another similar study investigated the impact of different charging strategies on the adoption of electric vehicles (Wee et al. 2019). The study found that providing free public charging and incentivizing home charging can significantly increase the adoption of electric vehicles. The study also found that optimized charging schedules can play an important role in reducing the cost and emissions of EV ownership, particularly when combined with renewable energy sources. The findings suggest that policymakers should consider these factors when developing policies to promote the adoption of electric vehicles and the optimization of charging schedules.

In 2018, the International Energy Agency (IEA) published a report analyzing the potential impact of policy measures on the adoption of electric vehicles and the deployment of charging infrastructure. The report concluded that policy measures supporting the use of smart charging technology and optimized charging schedules could accelerate the transition to a low-carbon transport system and reduce the cost of EV ownership. However, the effectiveness of these policy measures is dependent on the availability of charging infrastructure and the behavior of EV drivers. Therefore, the study highlights the importance of developing policy measures that support the adoption of smart charging technology and the optimization of charging schedules to realize significant economic and environmental benefits (IEA 2018).

Finally, user preferences are an important consideration when developing optimal EV charging schedules, with research by the Electric Power Research Institute finding that EV owners prefer to charge their vehicles during the evening and overnight hours when electricity rates are lower (EPRI 2017).

These studies highlight the importance of considering multiple factors when developing and implementing optimized charging schedules for electric vehicles. The findings suggest that factors such as driving behavior, charging infrastructure, and electricity costs should be considered to maximize the economic and environmental benefits of optimized charging schedules. Policymakers and EV owners should also consider the impact of charging strategies on the adoption of electric vehicles and the potential for renewable energy sources to further reduce the cost and emissions of EV ownership.

2.2 EV Total Driving Time

In the formulation of an optimized charging schedule, the total driving time in which a fully charged EV battery can travel is essential to understanding the points in which recharging is required. To calculate the total driving time of an electric vehicle (EV), several factors must be considered. The battery capacity is a key factor that reflects the amount of energy the battery pack can store and supply to the motor. Battery capacity is typically measured in kilowatt-hours (kWh). Additionally, driving efficiency and speed are essential variables. Driving efficiency determines how much energy is required to travel a certain distance and is affected by several factors such as vehicle weight, aerodynamics, tire type, and driving style. Moreover, driving speed is an important variable to consider since it has a direct correlation with energy consumption.

2.3 EV Charging
Charging electric vehicles (EVs) is an essential aspect of owning an EV as it determines the amount of time the vehicle can operate before needing a recharge. Home charging can be accomplished by utilizing a Level 1 or Level 2 charger, which typically takes several hours to fully charge the battery. Public charging stations, on the other hand, can offer faster charging rates, such as Level 3 DC fast charging, which can provide an 80% charge in as little as 30 minutes. Tesla, one of the major EV manufacturers, has its own proprietary fast charging network known as Supercharging, which enables Tesla owners to recharge their vehicles swiftly while on long road trips. Superchargers use direct current (DC) charging and can offer up to 170 miles of range in just 30 minutes of charging. Nevertheless, overusing Supercharging can negatively affect the battery health, so it is recommended to use it sparingly and rely on home or public charging whenever possible (US DOE 2021). The availability of charging infrastructure is crucial to support the widespread adoption of EVs. Thus, governments, automakers, and private organizations are investing in building public charging infrastructure networks to facilitate EV adoption and make charging more accessible to drivers. Additionally, the development of smart charging technology is enabling more efficient and cost-effective EV charging, by allowing users to schedule charging sessions during off-peak hours when energy prices are lower, reducing the overall cost of EV ownership.

According to the International Energy Agency (IEA), the number of publicly accessible charging points worldwide reached over 1.7 million in 2020, representing a significant increase from 60,000 in 2010. The IEA also reports that China, Europe, and the United States are the leading markets for EVs and charging infrastructure. In the United States, the Department of Energy (DOE) has launched the "EV Everywhere" initiative to promote the development of electric vehicle charging infrastructure. As of 2022, there were over 50,000 charging stations in the United States, with over 106,000 individual connectors available for public use (Han et al. 2016). The DOE has also funded research and development to improve EV charging technology and reduce charging times, resulting in the development of new fast-charging systems that can charge an EV in as little as 10 minutes. Smart charging technology is also being developed, with companies like ChargePoint and EVgo offering systems that allow EV owners to schedule charging during off-peak hours, which helps to reduce energy costs and improve the stability of the grid (Zhou et al. 2019).

2.5 Relevant Mathematical Concepts
To develop optimal charging schedules, objective functions, decision variables, and parameters/constraints must be considered. Objective functions are mathematical expressions that define the optimization problem's goal, such as minimizing the cost of EV charging or maximizing the use of renewable energy sources. Decision variables are the inputs that can be changed to achieve the objective function, such as the charging start time, charging duration, or charging rate. Parameters and constraints are the conditions that must be satisfied during the optimization process, such as the EV battery capacity, available charging infrastructure, and the user's driving schedule.

To develop optimal EV charging schedules, objective functions can be defined based on the user's charging preferences, energy costs, and the availability of renewable energy sources. Decision variables can then be adjusted to achieve the objective function while satisfying the parameters and constraints, such as limiting charging during peak energy demand periods or ensuring that the EV is fully charged before the user's next trip. Policymakers and stakeholders can develop optimal EV charging schedules that minimize the cost and emissions of EV ownership, promote the use of renewable energy sources, and enhance the overall efficiency of the energy system.

3. Methods
3.1 Solution Approach
The first step in the process of optimizing the EV charging is to accurately define the parameters of each of the cases that will be optimized. The most impactful parameter will be defining the weekly schedule of individual; this includes time where the EV can be charged, when the individual must be driving, and time where there are consequences for seeking charging. This is critical as it will serve as the largest constraints to the system as well as defining the system boundaries. After the schedules have been defined, the parameters that dictate the quality and quantity of charging will be defined from literature. This encompasses the rate at which the EVs can charge, the cost to charge, the capacity of the EVs, etc. These parameters can also be changed by each case to accurately fit the

system, such as reducing the EV capacity during the winter months. As previously mentioned, the results of this study tabulated, and the differences in performance based on parameters are correlated to find what constraints and parameters are the most impactful to the system. This will lead to conclusions on which parameters are the most important to consider when a given individual is seeking to use their EV more optimally.

3.2 Solution Assumptions

As the development of EV charging schedules need to account for a multitude of factors that are unique to each individual user, this paper considers three different weekly schedules, varied based on EV use frequency. The three schedules are formulated based on the weekly driving needs of a user that is a senior citizen (infrequent use), a user that a short-distance commute to work (moderate use), and a user that has a long-distance commute to work (frequent use). The total driving time in a week for each user is 10 hours, 22 hours, and 32 hours, respectively. The weekly driving needs of users will form the foundation of the optimized charging schedules as it will dictate the location and time in which the EV is available for charging.

In the three optimal charging schedules, all calculations are based on users driving a Tesla Model 3, which is the most popular EV model as of 2021 (EPRI 2017). Moreover, a constant speed of 50 miles/h throughout all driving activities is assumed.

4. Data Collection

4.1 Total Driving Time

The depletion rate of a Tesla Model 3 was calculated using data related to the Tesla Model 3 battery pack. According to Tesla, Inc., the Model 3 is equipped with a high-capacity lithium-ion battery pack that delivers an estimated efficiency of 3.5 miles per kWh (US EPA 2021). The battery pack comprises thousands of individual cylindrical battery cells connected in series and parallel to achieve the desired voltage and capacity. The battery pack has a total energy capacity of 75 kWh, which is one of the highest in its class.

To estimate when the total driving time of a Tesla Model 3 from a full charge, the total distance range will need to be computed first.

$$total\ distance\ range = 75\ kWh \times 3.5\frac{miles}{kWh} = 262.5\ miles$$

If an average driving speed of 50 miles per hour is assumed, the total driving time of a Tesla Model 3 is:

$$262.5\ miles \div 50\frac{miles}{hour} = 5.25\ hours$$

Hence, after a full charge and assuming a constant speed of 50 miles per hour, the total driving time is 5.25 hours. It is important to note that this calculation is only an estimate and is subject to variations depending on specific driving conditions and the vehicle's configuration. Therefore, it is essential to acknowledge that this estimated driving range of a Tesla Model 3 will be used as a reference point in the development of the optimized charging schedules to form adequate guidelines for calculations, and may not reflect the actual driving range achievable in real-world scenarios. Further, as the system was defined on a time basis, it was assumed that 1 hour of driving equates to a 19% decrease in the battery of the EV linearly.

4.2 Formulation of Problem

To formulate the charging problem, the system can be interpreted as a scheduling problem: when is it most optimal to charge the EV based on the usage. The main goal of the charging profile is to match the usage profile such that the difference is minimized. This was done using the Python package pyworkforce which uses the principle of minimum absolute difference. Minimum absolute difference with scheduling can be defined as an optimization problem where the goal is to choose pre-defined shifts to have the smallest difference from the resources defined. For the purposes of this paper, the resources are the amount that needs to be charged or the percentage of battery consumed from driving. The shifts are windows in time where the EV can be charged which would in turn increase the percentage of the battery. The main constraint added to the model was the amount that could be charged in an hour. This would influence how fast the charging could counter the effects of discharging. An optimal solution is defined as a solution that would match the driving profile the closest. This can never be a perfect fit as the EV cannot charge while it is being driven, thus optimization is extremely valuable.

4.3 Battery Usage Profile

Creating the driving profile was pivotal to creating a suitable model. This profile would represent the battery percent consumed over a week of driving. This profile would be different for everyone, so for the purposes of this paper three separate profiles were created, one for a short commute, one for a long commute, and one for a senior citizen. Below is a visualization of the driving profile for the short commute (Figure 1) individual; it can be noted that as time goes on, consumption only increases and that horizontal lines signify time where there is no driving.

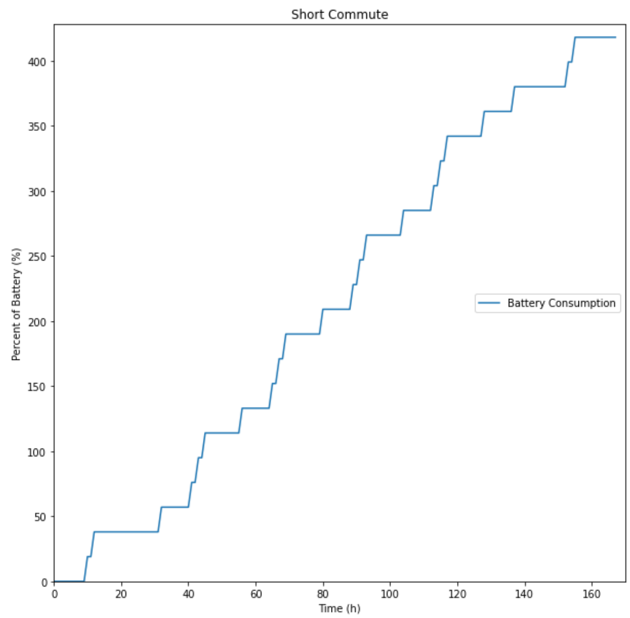

Figure 1. Driving profile for a short commute driver.

4.4 Defining Charging Windows

To represent the real world, charging windows were created to represent periods of time where the EV could be charged. These windows can simply be thought of as times where the EV is plugged in, and in which the battery will increase. Again, to align with the real world, there are no charging windows in the middle of the night during working hours or activities, only at times where it would be, it would be feasible for the individual to charge their EV. Additionally, the windows were modified if there was an opportunity for the individual to charge at a supercharger. For the purposes of this model, it was assumed that the supercharger could charge twice as fast as regular charging. More specifically, it was assumed that regular charging could recover 50% of the EV battery while supercharging could recover 100% of the EV battery in each hour. These different windows were added on to the individual's schedules.

5. Results and Discussion

5.1 Creating Optimized System

Solving the system requires utilizing the Python package pyworkforce with the appropriate input profiles and windows. A Python notebook was created to take in this data such that the problem could be solved. By creating profiles and windows for each of the different systems, this allowed for the problems to be solved individually. After setting up the scripts, the system was optimized, and solutions were found for each of the profiles which can be seen below.

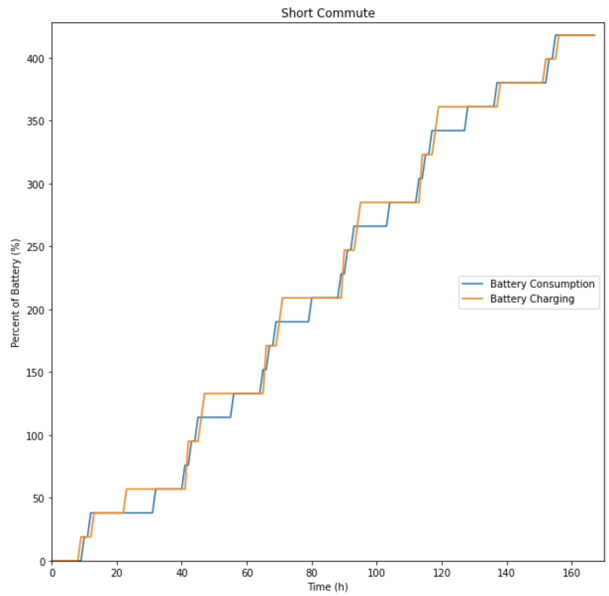

Figure 2. Optimized charging profile for a short commute driver.

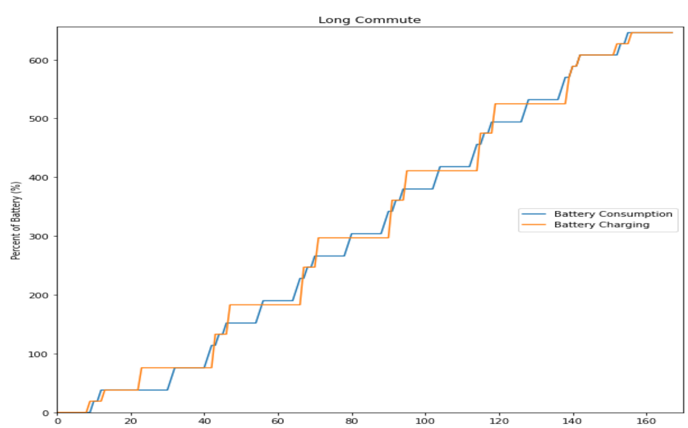

Figure 3. Optimized charging profile for a long commute driver.

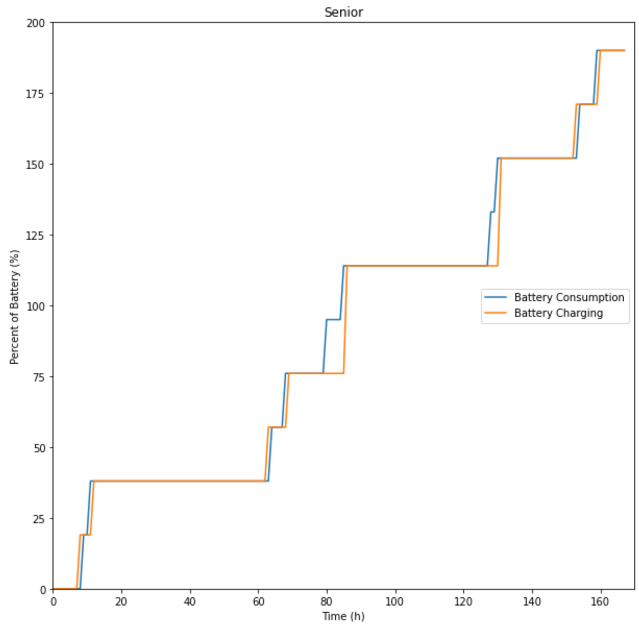

Figure 4. Optimized charging profile for a senior driver.

5.2 Optimized Charging Profiles

These profiles can be further interpreted into what time windows the EV should be charged in and what percentage the EV battery should be charged to within these windows. Using a spreadsheet to denote each hour within a week yields the following tables in which the yellow represents a time window where the EV should be charged, and the numbers represent the percentage of the EV battery that should be charged during that window. It is important to note that at any point where there is a value above 50, the EV is utilizing supercharging.

Time	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
00:00							
01:00							
02:00							
03:00							
04:00							
05:00							
06:00							
07:00							
08:00		Drive to work	Drive to work	Drive to work	Drive to work	Drive to work	19
09:00	19						Drive to gym
10:00	Drive to grocer						
11:00							Drive home
12:00	Drive home	Work	Work	Work	Work	Work	19
13:00	19						
14:00							
15:00							
16:00							
17:00		Drive home	Drive home	Drive home	Drive home	Drive home	
18:00		38	38	38	38	19	
19:00		Drive to gym	Drive to gym	Drive to gym	Drive to gym		
20:00							
21:00		Drive home	Drive home	Drive home	Drive home		
22:00		19	19	19	19		
23:00	19	19	19	19	19		

Figure 5. Optimized charging windows and amounts for short commute driver.

Time	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
00:00							
01:00							
02:00							
03:00							
04:00							
05:00							
06:00							
07:00		Drive to work	Drive to work	Drive to work	Drive to work	Drive to work	19
08:00	19						
09:00	19						Drive to gym
10:00	Drive to grocery store						
11:00		Work	Work	Work	Work	Work	Drive home
12:00	Drive home						19
13:00							
14:00							
15:00							
16:00							
17:00		Drive home	Drive home	Drive home	Drive home	Drive home	
18:00							
19:00		57	64	64	64	45	
20:00		Drive to gym	Drive to gym	Drive to gym	Drive to gym	19	
21:00							
22:00		Drive home	Drive home	Drive home	Drive home	19	
23:00	38	50	50	50	50		

Figure 6. Optimized charging windows and amounts for long commute driver.

Time	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
00:00							
01:00							
02:00							
03:00							
04:00							
05:00							
06:00							
07:00							
08:00	19			Drive to volunteer		Drive to grocery store	
09:00	Drive to church						19
10:00						Drive home	Drive to son's house
11:00	Drive home					38	
12:00	19						
13:00				Drive home			
14:00				38			
15:00			19				Drive home
16:00			Drive to daughter's house				19
17:00							
18:00							
19:00							
20:00			Drive home				
21:00			19				
22:00							
23:00							

Figure 7. Optimized charging windows and amounts for senior driver.

6. Conclusion

There are many conclusions that could be drawn from the optimized results of this paper. Firstly, since the objective function is to minimize the difference between the resource profile and the associated charging windows, the model preference is always having a full battery rather than letting the battery get to lower values and getting a larger charge. This can be not as ideal as many drivers would prefer to charge fewer times in the week and for larger charges than many small charges throughout the week. As well, the model prefers to charge very close to or after driving instances such that it recuperates or matches the profile very closely. This could potentially lead to issues for the drivers as they don't want to charge prior or immediately after driving and rather have designated times to charge their EV. The long commute profile is the only profile in which supercharging is utilized. In both the short and senior profiles there is never a charging window that goes above 50%, this is likely is due to the long commute profile having 4 hours of driving before any opportunity to charge the EV whereas the short and senior profiles only ever had two hours of driving in between charging windows. Lastly, it can be seen in every single profile that the charging values exceed that of the consumed values. Although from a scheduling perspective this would be desirable as it is minimizing the absolute difference, this is not feasible in the real world. As a battery only has a finite amount of storage it cannot exceed 100% of the charge, this means that anytime the charging profile surpassed the driving profile, the real-world battery would be capped at 100% and thus the full value from that charging window would not be utilized.

In consideration of the three different profiles tested, the senior profile provided a charging profile that was the most feasible. There were very few times where the charging profile exceeded the driving profile as this is a problem mentioned above. However, the long commute profile made best use of the superchargers as the model relied on using the superchargers after four hours of commuting during the day. When comparing the short commute and long commute profiles, they share many similarities to the times of charging with the main differences being the amount of charged as would be expected as the long commute drives further.

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Biographies

Aleksi Luoma is a recent chemical engineering graduate from the University of Waterloo. Holding a BASc, Aleksi completed six internships during his studies at Waterloo focusing on process engineering in a variety of fields including wastewater treatment, oil refining, and cell manufacturing. At Waterloo his capstone project focused on creating a novel process to recycle expanded polystyrene which was awarded for innovation in sustainability. After leaving Waterloo, he joined the cell manufacturing team at Tesla where he continues to work towards creating a sustainable future through advancing electric vehicles.

Loria Ou is a recent graduate in the field of Chemical Engineering. In earning her BASc in Chemical Engineering from the University of Waterloo, she concentrated her studies in Process Modelling, Optimization, and Control, alongside a minor in Management Sciences. Throughout her studies, she successfully completed six internships, exploring data analytics and process optimization in industries such as pharmaceuticals, food/beverage manufacturing, and cosmetics. Currently, Loria is a Risk Analyst on the Enterprise Risk Management team at Infrastructure Ontario, where she advances organization-wide risk reporting and management.

Ali Elkamel is a Full Professor of Chemical Engineering. He is also cross appointed in Systems Design Engineering. He holds a BSc in Chemical Engineering and BSc in Mathematics from Colorado School of Mines, MSc in Chemical Engineering from the University of Colorado, and PhD in Chemical Engineering from Purdue University. His specific research interests are in computer-aided modeling, optimization, and simulation with applications to energy planning, sustainable operations, and product design. His activities include teaching graduate and undergraduate courses, supervising post doctorate and research associates, and participation in both university and professional societal activities. He is also engaged in initiating and leading academic and industrial teams, establishing international and regional research collaboration programs with industrial partners, national laboratories, and international research institutes. He supervised over 120 graduate students (of which 47 are PhDs) and more than 45 post-doctoral fellows/research associates. He has been funded for several research projects from government and industry. Among his accomplishments are the Research Excellence Award, the Excellence in Graduate Supervision Award, the Outstanding Faculty Award, and IEOM Awards. He has more than 425 journal articles, 175 proceedings, 50 book chapters, and has been an invited speaker on numerous occasions at academic institutions throughout the world. He is also a co-author of six books.