DISSERTATION

OPTIMIZATION OF SUSTAINABILITY AND RESILIENCE FOR TRANSPORTATION PROJECTS

Submitted by

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ABSTRACT

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The state of America's infrastructure is old and has been deteriorating and is in need for severe rehabilitation and maintenance. The population has been increasing which has increased the demand for new transportation projects over the last decade. Therefore, it is essential to not just construct new transportation projects but invest in the rehabilitation and maintenance of the existing infrastructure. The transportation sector has the highest greenhouse gas (GHG) emissions among all infrastructure projects. In the transportation sector, the roads and highways subsector have the highest associated emissions which calls for projects in this subsector to be more sustainable. Concurrently, it has been observed that the frequency of natural disasters has increased exponentially in the last few decades which has increased the need to be more resilient. Sustainability and resilience are intertwined but different concepts that need to be explored and analyzed together. Both sustainability and resilience have been quantified using a variety of different methods, and rating system have been one of the most common and widely used methods across the globe for infrastructure projects. In North America (especially the US), the ENVISION rating system created through join efforts of the Harvard graduate School of Design's Zofnass Program of Sustainable Infrastructure and the Institute of Sustainable Infrastructure, has been the most widely used rating system for various infrastructure projects, especially transportation projects.

Often, achieving sustainability and resilience is associated with a higher cost. This research proposed optimizing sustainability and resilience while minimizing the life cycle cost (LCC) and GHG emissions using the NSGA-II algorithm. It takes input of all possible strategies within the different dimensions of sustainability and resilience and uses the abovementioned algorithm to determine a list of pareto optimal solutions. These solutions represent a space of acceptable solutions which have high sustainability and resilience while also having low GHG emissions and LCC.

This model is intended to assist stakeholder in making decisions to improve the sustainability and resilience while promoting a life cycle thinking. It also provides a unique database creation idea for keeping all sustainable and resilient strategies for different infrastructure projects in one place which can promote an open access feature as more transportation agencies and stakeholders buy-in to the idea of using this model.

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I want to thank my family whose support has been pivotal in overcoming challenging times and rejoicing achievements. My colleagues in the graduate school office have been a great support over the course of my graduate studies and I want to acknowledge their patience and encouragement through these years.

DEDICATION

This dissertation has been dedicated in memory of my mother, Neelam Verma, whose support and love still shines until this day.

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1 Introduction

Transportation systems are essential to promote micro and macroeconomic objectives of our community. They provide employment, add value the economy, improve accessibility to goods and services, and link various economic sectors among many other functions (Rodrigue et al., 2016). The United States (US) transportation infrastructure has been divided into aviation, bridges, inland waterways, levees, ports, rail, roads, and transit according to the ASCE report card (ASCE, 2021d). Among all, roads and highways are the most dominant mode of transportation in the U.S with a passenger transport share of 86.93%, compared to air carriers with 11.81%, and railways with just 0.77%. For cargo transport, roadways account for 40.34% while railways, waterways, and air transport accounts for only 26.13%, 7.47%, and 0.19% respectively (ASCE, 2017, 2021d). Hence, this research focuses on roads and highways as the primary transportation infrastructure asset. These transportation-related services are intended to deliver continuous service for close to a century or more, and therefore there is an urgent need to ensure that the transportation infrastructure created and maintained is sustainable and resilient. With depleting natural resources, increased greenhouse gas emissions and an increasing frequency of natural disasters, it is imperative that sustainability and resilience should be incorporated in all infrastructure projects (Ritchie, 2020).

Several quantitative measures to measure sustainability have been created in the past few decades, however, infrastructure rating systems have actively helped in championing the adoption of sustainability in infrastructure projects (and transportation projects in specific). ENVISION rating system has been at the forefront of all rating systems in North America and it has been used as the baseline to create the ASCE sustainability standard for infrastructure rating systems. ENVISION rating system has been divided into several categories that focus on different dimensions of sustainability like social, economic, and environmental. ENVISION rating system has been used as the method of quantifying sustainability in this research

Although the adoption of sustainability and resilience is at the forefront of global priorities, there still exists disagreement in terms of the terminology definitions and the quantification of sustainability and resilience of infrastructure projects (transportation projects to be specific). More importantly, transportation projects have been struggling to adopt sustainability and resilience due to budget constraints and the inability of economic feasibility forecasting. Conducting a life cycle cost analysis (LCCA) can assist with economic feasibility forecasting, but seldom it is under consideration to assess the various strategies to build a transportation project. There is an ongoing debate between having a lower initial cost and having a lower LCC, and it is challenging to get consumer buy-in for products that have a higher initial cost and a lower LCC. Though research efforts have been made in the previous years to develop assessment techniques such as LCC and quantification metrics for sustainability and resilience, a model assisted decision making framework that can facilitate an ease of selection of strategies to build a transportation infrastructure does not exist, presently.

Therefore, in this research, a multiobjective optimization approach has been a selected *to address the competing interests of stakeholders, such as sustainability, resilience, and life cycle cost under budget constraints*. A comprehensive literature review is conducted to understand the developments made in this area of research and discern the various research gaps to address the above main objective. These research gaps helped in developing the research questions and the main research objectives as defined in sections 2.7 Research gaps and problem statement and 2.8 Research questions and objectives.

2 Literature review

2.1 Development of transportation systems

The growth of transportation systems can be attributed to population growth which demands better interconnectivity for transport of people, goods, and services (CDOT, 2018). The 1800s have seen major developments in US transportation infrastructure with the increase of dirt roads around US and the extensive usage of steamboats, as precursors to the national economic development. The period from 1850s to 1930s has been termed as the “age of rail” wherein streetcars, subways, and intercity trains thrived. The US cities started becoming car-centric towards mid-twentieth century which was attributed to the rise of the automobile sector and an increase in the standard of living of the average American family. This led to a decline in the ridership of streetcars which were ultimately abandoned around the early 1960s (English, 2018). With more cars on the roads, the need to develop the roads and highways infrastructure received Congress support in 1956 with the approval of the Interstate Highway Act which approved mass funding for all high-speed highways. Through this federally-aided Act, around 41,000 miles of highways were constructed, thus instituting the national freeway network (FHWA, 2021).

2.1.1 Overview of the US transportation systems

The United States transportation infrastructure has been divided into aviation, bridges, inland waterways, levees, ports, rail, roads, and transit according to the ASCE report card (ASCE, 2021d). Railways have the highest grade of B and the transit has the lowest grade of D-, among all infrastructure systems.

Graded at a D+, aviation infrastructure experiences over three million passengers every day, providing about 700,000 jobs (2012 data) and contributing 5.2% to the US GDP according to the Federal Aviation Administration (FAA)) (ASCE, 2021b; Bureau of Transportation Statistics, 2021; FAA, 2020). Bridges in the US have been graded at a C as 7.5% out of a total of 617,000 bridges are structurally deficient with expected rehabilitation costs of $125 billion (ASCE, 2021c). Spanning over 23,000 miles, active waterways carry over 830 million tons of cargo every year. These inland waterways system in the US have been graded at a D+ (ASCE, 2021e). The US has 300 ports (overall graded at a B-) that generate a revenue of $5.4 trillion and accounts for about 26% of US economy (American Association of Port Authorities, 2019; ASCE, 2021f). Railways have the highest grade of a B and it delivered more than 1.4 billion tons of freight in 2018 and about 32.5 million passengers in 2019; it is also the only infrastructure system that has been making significant investments to ensure timely maintenance (ASCE, 2021g). The roads infrastructure has been termed as being chronically underfunded which has been one of the causes of ever-increasing fatalities, therefore it has been graded at just a D (ASCE, 2021h). The US Transit system has been given the lowest grade of D- among all other infrastructure systems due to severely underfunded programs which totals about $176 billion in backlogs (ASCE, 2021i).

Although different transport modes make-up the entire US transportation infrastructure system, roads and highways is the most dominant mode. For passenger transport, highways account for a share of 86.93%, air carriers with 11.81%, and railways with just 0.77%. For cargo transport, roadways account for 40.34%, railways with 26.13%, waterways with 7.47%, and air transport with 0.19% (ASCE, 2017, 2021d). Hence, this research focuses on roads and highways as the primary transportation infrastructure asset.

The infrastructure investment spending portion has been decreasing since 1965 (Stupak, 2018). In 2017, the US spent around $441 billion (comprising 2.3% of the total GDP) on infrastructure with an anticipated $1.5 trillion investment gap until 2025 (CFR, 2018; HCB, 2019). The Highway trust fund which accounts for all sources of revenue (gas and related fuel tax, diesel and kerosene, heavy trucks and trailers sales tax, heavy vehicles annul use tax) from operating roads and highways received a total of $41 billion for 2018 (TPC, 2018) which is vastly insufficient as compared to the $800 billion of estimated expenses by the US Department of Transportation (USDOT) for just performing maintenance of existing bridges around the US (CFR, 2018).

2.1.2 Major Global and national transportation projects

This section will highlight several global examples of leading roads and highway projects to reflect the volume of developments around the world. In Africa, the Transportation and Urban Mobility project in

Senegal rehabilitated a 107.5-mile road stretch to reduce the travel time for more than a million people and improve the mobility by paving urban roads. In Morocco, the Urban Transport Program is aimed at creating bus corridors that will potentially benefit more than 130,000 people and facilitate the collaboration between municipalities. The National Rural Transport Program in Nepal is aimed at connecting rural communities by improving the reliability of the rural road infrastructure. The Transport and Trade Facilitation Project in the Western Balkans covering six countries (Albania. Bosnia and Herzegovina, Bulgaria, Croatia, Kosovo, and North Macedonia) will deploy intelligent transport systems to improve the performance monitoring (World Bank, 2021). Though great developments have been seen in smaller developing countries around the world, as evident from examples discussed above, monumental expansion has been planned and being executed in two of the largest developing economies in the world (India and China). According to the India Brand Equity Foundation (IBEF), the Government of India (GOI) approved a budget of $14.85 billion in the latest union budget to construct 23 new national highways by 2025 (IBEF, 2021). China's $900 billion silk road project is one of the biggest in the eastern hemisphere of the world aimed at invigorating the silk road to bolster the trans-Eurasian trade infrastructure and generate up to $8 trillion of infrastructure value in 68 countries (Bruce-Lockhart, 2017). These developments around the world show the impactful benefits created by developing roads and highways.

Examples specific to the US have also been mentioned as this research predominantly focuses on the US market. The five biggest roads and highways projects in the US (in 2016) have been estimated at $22.5 billion. The I-95 widening project in Connecticut was estimated at $11.2 billion aims to relieve the congestion problems. San Gabriel Valley Route 710 tunnel was estimated at $5.6 billion to relieve the Los Angeles traffic problem. The I-4 Ultimate Project in Florida has been in progress to offer a bypass between northern and southern parts of Florida while minimizing the environmental impacts in the area. Mon-Fayette Expressway extension in Pennsylvania has been estimated at $1.7 billion and will be connecting Pennsylvania to downtown Pittsburg. Lastly, I-77 express lanes in North Carolina is estimated at $647 million which will add 26 miles of variably priced lanes (Jaffe, 2016).

These transportation-related services are intended to deliver continuous service for close to a century or more, and therefore there is an urgent need to ensure that the transportation infrastructure created and maintained is sustainable and resilient. With depleting natural resources and increased frequency of natural disasters, it is imperative that sustainability and resilience should be incorporated in all infrastructure projects.

2.2 Sustainability

Sustainability is derived from a German term, Nachhaltigkeit (meaning sustained yield), which was first used by Hans Carl von Carlowitz in his book, Sylvicultura Oeconomica (sustainability in forestry management) (Carlowitz, 1713; The World Energy Foundation, 2014). The more recent definition of sustainability has been derived from the United Nation's (UN) Brundtland Report of 1987 that posited "sustainable development meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987). Following the UN's report, Clinton's administration widely endorsed sustainability in biology, economics, sociology, urban planning, and ethics among many other domains (Basiago, 1995). Costanza and Patten (1995) emphasized system definition, duration of sustenance, and monitoring of system sustenance as essential components when defining sustainability. The United States Department of Agriculture (USDA) defined sustainability as a conscious effort to address present inhabitants' needs while preserving resources for the prosperity of future generations (USDA, 2007). More recently, the Environmental Protection Agency (EPA) defined sustainability as "creating and maintaining the conditions under which humans and nature can exist in productive harmony to support present and future generations" (EPA, 2011).

The three main components of sustainability, namely, social, economic, and environmental were encapsulated into the triple bottom line (TBL), a term coined by John Elkington in 1997 (Elkington, 1997). This three-dimensional breakdown (TBL) has been widely accepted by researchers and prominent sustainability-driving organizations across the world (Basiago, 1998; GLOPP, 2012; Ilic-Krstic et al., 2018; USNESCAP, 2015). Besides the basic bottom line categorization, previous studies have suggested other dimensions of sustainability. Sverdrup and Svensson (2002) defined three dimensions of sustainability as natural sustainability (maximum long-term natural resource usage), social sustainability (inherent stability of social organization and its components subject to system oscillations), and economic sustainability (accounts for mass balance and economic feedback principles). Goodland (2002) identified human, social, economic, and environmental as four main sustainability types. Vos (2007) added policymaking which exceeds the bounds of existing regulations as an integral part of creating a sustainable system. The TBL categorization was later adopted as the sustainability reporting guideline by the global reporting initiative (Blackburn, 2007). Thereafter, the American Institute of Chemical Engineers (AIChE) sustainability index provided a standardization of sustainability by defining seven dimensions namely, environmental performance, safety performance, product stewardship, social responsibility, value-chain management, strategic commitment, and sustainability innovation (Cobb et al., 2009).

Several initiatives have been considered and adopted in different capacities to incorporate sustainability into projects. The Paris Climate Change agreement and the formation of Sustainability Development Goals (SDGs) have facilitated the adoption of the sustainability's TBL (United Nations, 2021; United Nations Department of Economic and Social Affairs, 2021). The Energy Transitions Commission (ETC) has aimed to develop energy systems considering climate repercussions and achieving net zero in the next 30 years (ETC, 2021). The Delhi Metro Rail Corporation (DMRC) created the metro rail infrastructure in New Delhi, India, using the key TBL principles and helping reduce the greenhouse gas (GHG) emissions by 630,000 tons (DMRC, 2017; Runde et al., 2019). In Manhattan, US, a decommissioned rail infrastructure was converted into a green space to improve the social mobility and enhance the air quality in the local area (United Nations Environment Programme, 2020).

In addition to the broader initiatives at the global and the US level, several construction-specific initiatives have been proposed in many research studies. Yılmaz and Bakış (2015) suggested a conscious design charrette incorporating sustainable materials to lower the social, economic, and environmental impacts. The construction industry has been riddled with various issues such as the contribution to global warming, loss of biodiversity and natural habitats, air pollution, acidification, toxicity, deforestation, and water resource depletion, wherein improvement of each can improve the sustainability (Khatib, 2016). Therefore, Koutsogiannis (2018) suggested various benefits of investing in construction sustainability, namely, cost reduction, increased productivity, improved health, waste minimization, efficient materials usage, environmental protection, noise avoidance, improved quality of life, and potential investments in the sustainability market.

2.2.1 Social Sustainability

Previous research has minimally defined social sustainability as “meeting the basic needs and addressing underdevelopment” (Vallance et al., 2011). Alternatively it has also been defined as “maintaining and preserving preferred ways of living or protecting particular socio-cultural traditions” (Vallance et al., 2011). Social sustainability relates to the relationships within a society wherein the interactions between nature and society are promoted (Littig & Griessler, 2005). Karbassi (2019) defines social sustainability as “identification and management of business impacts (positive and negative) on people. The Institute for Sustainable Futures (2019) suggested that social sustainability occurs when the formal and informal process, systems, structures, and relationships actively support the capacity of current and future generations to create healthy and livable communities.

Social sustainability has been divided into categories, termed as “dimensions” by most researchers. Bramley and Power (2009) categorized social sustainability into social equity which accounts for local services encompassing access to jobs and affordable housing, and community sustainability which encapsulates the interaction between residents, participation in collaborative communities, pride and sense of place, resident stability, and security. Vallance et al. (2011) further defined social sustainability types as developmental (concerned with meeting basic needs, inter- and intra-generational equity), bridge (changing behavior to achieve bio-physical environmental goals), and maintenance (social acceptance or what can be sustained in social terms). Dempsey et al. (2011) identified five dimensions of social sustainability namely, social interaction/social networks in the community, participation in collective groups and networks in the community, participation in collective groups and network in the community, community stability, pride/sense of place, and safety and security. Valdes-Vasquez and Klotz (2013) divided social sustainability into four areas – community involvement (public constituencies in governmental and private decisions), corporate social responsibility (accountability of an organization in caring for all of the stakeholders affected by its operations), safety through design (ensures worker safety by eliminating potential construction/operation safety hazards during the design phase), and social design (improving the decision-making process of the design team and the intended use of the project by the final users). Mani et al. (2016) identified supply chain social sustainability dimensions as adequate housing, non-discrimination, philanthropy, safety, equity, human rights, creation of employment opportunities, wages, labor practices, poverty, health and hygiene, hunger, ethics, child and bonded labor, and educational opportunities. Finally, Missimer et al. (2017) suggested trust, common meaning, diversity, capacity of learning, and capacity of self-organization as essential aspects to sustain social sustainability.

It can be observed from the different categorizations of social sustainability that many of the dimensions contribute towards the socioeconomic factors of a society. Therefore, improvement of the socioeconomic factors such as community involvement, adequate housing, hunger, and safety among many others can assist in improving not only the social sustainability, but also resilience to various disasters (Johnson, 2017; Mani et al., 2016; Valdes-Vasquez & Klotz, 2013).

Improving the social sustainability can be thought of as a combination of the siloed yet coordinated efforts to improve its dimensions. A few examples depict how practical implementation of various measures and strategies can elevate the level of social sustainability. Karbassi (2019) suggested a business-level focus on worker wellbeing and human rights, creating an inclusive environment, and professional development opportunities to further the goals of social sustainability. In the transportation sector, social acceptance, public participation, social equity and public health, identity and heritage, safety and security, economic viability, and usability and efficiency have been defined as areas that require improvement to enhance social sustainability (Weaver et al., 2015). Foth et al. (2013) explored equitable distribution of benefits for transit systems by quantifying equity (accessibility, travel time etc. as metrics) and inferred that groups having a lower socioeconomic status have a higher need of social equity. Another research explored the social impacts of urban transportation innovations to verify their effects on improving the services provided to a community, improving the accessibility to the transportation system, and enhanced the community's use of public transport (López et al., 2019).

These examples provide insights into a few recent measures and strategies adopted in the construction industry and the transportation sector. It can be also concluded that improving the equity, health and wellness, and level of engagement of a community are quintessential to improving the social sustainability. While social sustainability (and its dimensions) is being enhanced, careful steps need to be taken to ensure that the impacts on the environment are minimized. Henceforth, the environmental sustainability has been detailed in the following section.

2.2.2 Environmental Sustainability

Environmental sustainability is aimed at improving the community welfare by protecting raw material sources and ensuring that the sinks for human wastes are not exceeded (Goodland & Daly, 1996). These sink can refer to either the geogenic (natural) or anthropogenic (manmade) locations and technologies which facilitate waste disposal (Kral et al., 2014). To support the above definition of environment sustainability, Goodland (1995) stated in earlier research that "wastes should be limited to the assimilative capacity of the environment", hence maintaining the natural capital. Hueting and Reijnders (2004), building on the same concept, further stated that in an environmentally sustainable system, the production levels should not threaten the living conditions of future generations. A different approach was followed by Holdren et al. (1995) to consider aspects of biophysical sustainability as being synonymous to the environmental sustainability. They aimed at making the biosphere sustainable by optimizing the resource usage by current and future generations while maintaining biodiversity and biochemical integrity. Morelli (2011) defined environmental sustainability as meeting the needs of the community while ensuring the non-exceedance of the ecosystem regenerative capacity and maximization of biodiversity. Kaswan et al. (2019)

considered environmental sustainability as the boundaries where humans can satisfy their current needs without compromising the quality of environment/ecosystem, to ensure its support for future generations. The essence of all these definitions show that this dimension of sustainability ensures optimal resource usage while minimizing ecosystem impacts and preserving and enhancing biodiversity. Major focal points associated with environmental sustainability are shifting towards promotion of the adoption of renewable resources, protection of ecosystem health, avoiding excess pollution, targeting welfare and not gross domestic product, and intergenerational decision-making facilitation (Pettinger, 2018).

Due to the vast nature and complexity of the environmental sustainability realm as a broad component of sustainability, various researchers have attempted to categorize environmental sustainability. Goodland and Daly (1996) suggested ecosystem integrity, carrying capacity ("the maximal population size of a given species that an area can support without reducing its ability to support the same species in the future."), biodiversity, and dealing with global issues as four objectives of environmental sustainability. An environmental sustainability task force identified five dimensions of environmental sustainability as environmental system, reducing environmental stress, reducing human vulnerability, social and institutional capacity component, and global stewardship (World Economic Forum - WEF - Global Leaders for Tomorrow Environment Task Force et al., 2002). These dimensions were further divided into 20 driving variables – air quality, water quantity, water quality, biodiversity, land, reducing air pollution, reducing water stress, reducing eco-system stress, reducing waste and consumption pressures, reducing population growth, basic human sustenance, environmental health, science and technology, capacity for debate, environmental governance, private sector responsiveness, eco-efficiency, participation in international collaborative efforts, reducing greenhouse gas emissions, and reducing trans-boundary environmental pressures (World Economic Forum - WEF - Global Leaders for Tomorrow Environment Task Force et al., 2002). Olewiler (2006) simplified the definition of environmental sustainability by considering the natural capital represented in the natural resources (renewable and non-renewable resources, ecosystems, and land) as the sole driver of environmental sustainability.. Irabien et al. (2009) divided environmental sustainability into two categories – natural resources sustainability (NRS), and environmental burdens sustainability (EBS). Moldan et al. (2012) divided the environmental sustainability into six areas – (1) climate systems, (2) human settlements, (3) energy systems, (4) terrestrial systems, (5) carbon and nitrogen cycles, and (6) aquatic systems. According to the US Department of Energy (USDOE), environmental sustainability has been divided into two areas – environmental compliance and environmental sustainability (USDOE, 2020).

Beyond categorizing and classifying environmental sustainability, there have been a plethora of initiatives to encourage and further improve the environmental sustainability efforts on different levels. Cowan et al. (2010) focused on improving the organizational environmental sustainability through leadership's commitment to sustainability, standardized reporting, third-party evaluation of sustainability programs, and obtaining ISO 14001 certification. The International Organization for Standards (ISO) created the ISO 14001 standard for improving organizations' environmental performance (ISO, 2015). Arora (2018) promoted environmental sustainability initiatives to ensure the survival of future generations and counter the effects of widespread pollution due to modern agricultural practices, temperature increase and its effects on polar ice caps, and the dire need for owners, contractors, and other stakeholders to start focusing on environmental sustainability. Owner organizations have been shifting to create environmentally sustainable infrastructure as it offers better consumer engagement, greater employee engagement, and long term strength (Jones, 2018). Malaysia provides a good example of promoting environmental sustainability in construction to reduce the irreversible impacts to the environment by integrating environmental considerations into planning development (Abidin, 2009). A statistical analysis conducted by Abidin (2009) showed a low to medium understanding and implementation of strategies to improve environmental sustainability. After the enactment of sustainable development goals and the Paris agreement (COP22), organizations have started thinking about lowering the environmental impact through different efforts and metrics such as monitoring the usage of natural resource and minimizing the carbon footprint (Boston College Center for Citizenship, 2020). Even though the above initiatives provide great references for enhancing the environmental sustainability, it was still lacking a comprehensive standardized frameworks to achieve sustainability goals. Therefore, several sustainability rating systems have been created to provide such framework. Montgomery et al. (2015) suggested the usage of transportation and infrastructure sustainability rating systems such as ENVISION, CEEQUAL, INVEST, Greenroads, and GreenLITES, to further transportation sustainability. Furthermore, they emphasized on sustainability through all four phases of the project starting with the planning criteria (including short and long-term planning), and through the project planning and design phase (including the project scope definition, conscious design that reduces environmental impacts), construction phase, and the operation and maintenance phase. Initiatives such as the National Environmental Policy Act (NEPA) has mandated the reduction of environment impact from transportation projects. Several energy related initiatives like E.O. 13783 (promotion of energy independence), Corporate Average Fuel Economy (CAFE), and alternate fuel and electric vehicle corridors have also resulted in the reduction of associated emissions (USDOT, 2021).

It is noted from the above initiatives that successful environmental impact minimization is dependent on the adoption of regulations that mandate organizations to provide serious consideration to the environmental aspects. Consequently, developments have been made to create rating systems which provide a standardized metric and act as a guidance document for improving environment sustainability across the different types of projects. While improving the social and environmental sustainability is paramount, it is essential to understand the economic impacts of the improvement measures. Thus, detailing the economic sustainability and its components becomes important in efficiently addressing and adopting sustainability measures.

2.2.3 Economic Sustainability

Since early ages, economic sustainability has been defined as the "maintenance of capital" (Goodland & Daly, 1996). Sheth et al. (2011) defined economic sustainability through a customer-centric approach wherein the status of customers' debt to burden ratio, earning pressures, and work-life balance are assessed. Popovic et al. (2013) have defined economic sustainability as an encapsulation of financial costs and benefits while Löf (2018) defined the economic sustainability as the life cycle cost of resource usage, wherein life cycle refers to the total service duration. More modern definitions of economic sustainability are linked to life cycle approaches and innovative financing techniques which promotes services that enhance the TBL of sustainability. Hence, LafargeHolcim Foundation (2019) defines economic sustainability, from an energy perspective, as the introduction of innovative financing techniques that uses circular economy of renewable energy generation wherein the "reinvestment of returns is returned to the common domain for collective benefit". Economic Sustainability has been recently referred to as "practices that support long-term economic growth without negatively impacting social, environmental, and cultural aspects of the community" (University of Mary Washington, 2020).

Economic sustainability can be challenging to understand as many of the definitions above relate to policy makers and organizational level applications. However, this economic sustainability needs to be further explored by understanding its components as detailed in several research studies. Sourani and Sohail (2005) broken down economic sustainability into – financial affordability, maintaining economic growth, using life cycle costing approach, creating and maintaining employment, supporting local economies, investment, use of key economic performance indicators, viability, profitability, competitiveness, productivity, and value for money. Isaksson (2005) proposed three categories of economic sustainability based on the Global Reporting Initiative (GRI) guidelines namely, direct economic impacts, indirect economic impacts, and sustainability costs of poor quality. Sheth et al. (2011) categorized economic sustainability as conventional financial performance (e.g., return on investment, return on equity, earnings per share, etc.) and economic interest of external stakeholders (e.g., improvement in economic well-being, standards of living, etc.).

As noticed in most of the recent definitions of economic sustainability, the concept of life cycle costing (LCC) became an integral part of economic sustainability. Therefore, plethora of research studies have been conducted over the past two decades in this area. LCC has been discussed in greater detail in a later section of this literature, yet it is worthy to mention a few instances in relation to economic sustainability. Jeswani and Azapagic (2012) assessed the economic sustainability of biodiesel usage by calculating its LCC including various costs such as the cost of raw materials, capital costs, and labor and maintenance costs. Popovic et al. (2013) adapted two dimensions of economic sustainability namely, capital costs (expenses incurred during the construction and other installation processes) and operating costs (expenses incurred daily/monthly/annually to keep a facility functioning) (Van der Vulten-Balkema, 2003).

The breakdown of economic sustainability into various categories and dimensions has facilitated the adoption of directed measures and strategies that aim to improve the economic sustainability. Spangenberg (2005) suggested numerous criteria for enhancing economic sustainability including but not limited to redundancy and diversity of economic structures, balancing the trade exchange between different economies, innovation potential, and development of positive conditions for economic sustainability. Bishop (1993) suggested implementing taxes on the use of natural resources to improve the economic sustainability. In the context of sustainable construction, the economic sustainability perspective accounts for a greater value for money, getting maximum output with minimum input, integration of short-term and long-term benefits, and improvement of stakeholder partnership and human quality of life (Zhou & Lowe, 2003). Consequently, LafargeHolcim Foundation (2019) shows the usage of savings during sustainable construction could be used for future reinvestments in resources. Finally, in the context of transportation infrastructure, transit-oriented development has been seen to reduce average household expenses, drive economic development, and increase housing affordability. Parking management can reduce instances and associated costs of urban redevelopment and rededication of land (EPA, 2019). Investments for the construction of new road and other transportation projects have been the focal point of many initiatives adopted by various governments as it provides access to several opportunities and services (Shen et al., 2018).

about the literature on the TBL of sustainability emphasized the need for designing and constructing in a manner that improves the social conditions, minimizes the environmental impacts, and leads to economic growth. Therefore, as the focus of this research study, it is imperative to this discussion to understand the need for sustainable transportation and the benefits it provides.

2.2.4 Need for Sustainable Transportation

Sustainable transportation has been defined as being green and low impacting to the environment (City of Vaughn, 2019). The transportation sector is responsible for around 8 billion tons of CO_2 eq. in greenhouse gas (GHG) emissions (Ritchie, 2020). Road transportation contributes the highest share of the total emissions (5.95 billion tons of CO_2 eq.), followed by aviation (950 million tons of CO_2 eq.), shipping (850 million tons of CO_2 eq.), and rail (200 million tons of CO_2 eq.) (Ritchie, 2020). Visualization of this data has been shown in Figure 1.

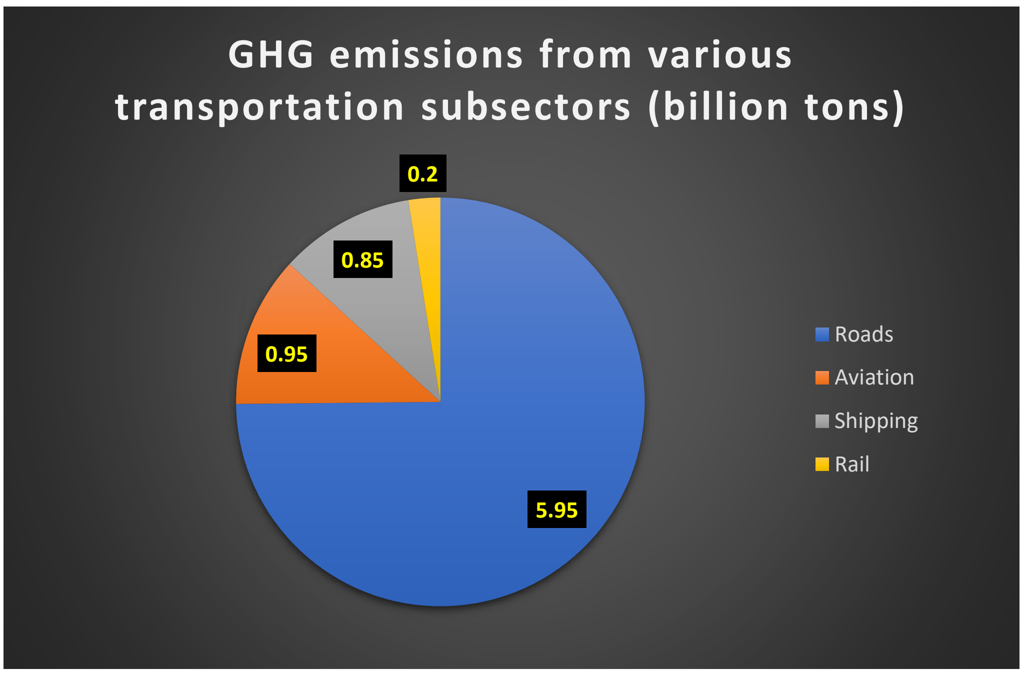

Figure 1: GHG emissions for the transportation sector

It should be noted from the above figure that the roads and highways generate the highest amount of emissions, and therefore they will be the focus of this research and will be further elaborated in the methodology section. Transportation projects have always had a greater impact on the environment as they affect air quality, water quality, climate and land usage (EPA, 2019). Though a majority of previous studies across numerous transportation projects over the world assess the environment impacts, only a few studies have addressed the social and the economic impacts of the transportation sector. Mobility issues for the disabled and elderly, forced relocation of a community due to a transportation project, and the lack of public awareness about potential future projects have been suggested as a few negative social impacts for transportation projects (Varlıer & Özçevik, 2015). Chamseddine and Ait Boubkr (2020) studied the literature comprehensively and noted several social impacts of transportation systems such as accessibility issues, health-related impacts (cardiovascular issues, traffic injuries and deaths, etc.), safety (inadequate safety, unreliable service, etc.), social exclusion, and inequity. The economic impacts of transportation systems have majorly been long-term, which often obscures the actual impact; for example, a shift in jobs may be perceived as a great short-term benefit, but the imposition of taxes to cover future operating deficits (Wachs, 2011). Therefore, it is essential to conduct a feasibility analysis and select the right project for the right location. Instances when the project is selected correctly, it can still lead to negative economic impacts due to its poor performance. Poor economic performance of transportation projects has been linked to an adverse effect on the economic activities, which reduces the value added for any region, lowers the economic opportunities, and worsens unemployment (Rodrigue et al., 2016). Recognizing a plethora of negative impacts on the TBL, it is imperative to address the need to make "sustainable transportation" as part of the discussion among various transportation agencies.

According to Replogie (1991), sustainable transportation accounts for "holistic approach to policy and investment planning to achieve a diverse and balanced mix of transport modes". Richardson (1999) elaborated the need to focus on sustainable transportation and defined it as systems that can save fuel, have low emissions, safe to use, less congested, and can sustain future generations through a combination of technological developments and policymaking as means to improve the transportation sustainability. Federal Highway Administration et al. (2005) suggested a cultural transformation to promote an integrated land use and transportation planning approach to further the innovation in sustainable transportation systems.

2.2.4.1 Benefits of Sustainable Transportation

Sustainable transportation is aimed at providing a lower environmental impact while increasing the capacity (size of transportation infrastructure), incorporating modern construction techniques, and usage of materials with low carbon content while maximizing the lifetime. Boschmann and Kwan (2008) found that sustainable transportation also creates social progress by changing the urban form, increasing the accessibility, and directing the efforts for city planning to improve social equity, social inclusion and quality of life. Litman and Brenman (2012) identified the improvement of social equity as one of the benefits of having sustainable transportation. Social equity, in regards to transportation, aims at minimizing discrimination against minorities, accommodating people with disabilities, support affordable housing in accessible locations, reducing traffic impacts on neighborhoods, transporting subsidies for seniors and disabled, and implementing smart growth land use policies. Mulley et al. (2013) further capitalized on the social equity principle to suggest that bike-ability is an integral part of sustainable transportation and emphasized its significant health benefits. More importantly, building sustainable transportation is an integral part of creating sustainable cities. For example, the density of a more sustainable Copenhagen is 4.8 times of Houston, but it generates just 1/10th the amount of CO_2 as compared to Houston (Lindau, 2016). Schaffer (2017) echoed a similar thought emphasizing the need for sustainable transportation to manage overall sustainable development. USDOT (2016) captured all previous studies by claiming that public transportation systems like transit help in improvement of air quality, reduction in greenhouse gas emissions, facilitation of compact development by conserving land and reducing travel demand, saving energy, providing socioeconomic benefits, and minimizing other environment impacts.

2.2.4.2 Examples of Sustainable Projects Globally

Global examples of sustainability in transportation have been discussed in this section to illustrate the unique approaches adopted across the globe. In Bogota - Columbia, the mayor, Enrique Penalosa, initiated a sustainable transportation system consisting of a Bus Rapid Transit (BRT) system with a ridership of 1.4 million passengers per day, a 212 miles of bike path, and more than 1000 parks. This transformation led to significant reduction of wait times in the traffic, lowered number of accidents, and a reduction in crime rate (Kete et al., 2008). In Indore India, a 6-mile BRT corridor is constructed to finance a much larger 70-mile network, shows that high cost investment is not needed to create sustainable transportation (Schiller, 2014). China created a Guangzhou Bus Rapid Transit that incorporates a bike-share system available at 113 bus stations, hence reducing emissions and catering towards millions of people's needs in a densely populated area (Zajechowski, 2016). The Canadian city of Vaughn has made significant strides in creating a sustainable transportation system with introduction of the York region transit with enhanced mobility (as part of the mobility plus program), extension of the Toronto Transit Commission subway by 5.4 miles, and the Go Transit service for greater Toronto and Hamilton areas (City of Vaughn, 2019).

2.2.4.3 Examples of Sustainable Projects in US

Since the focus of this research is on the US, a few examples of sustainable transportation projects in the US have been discussed in this section. It cannot be ignored that recent developments in battery technology have eased the adoption of electrical transportation modes. Sacramento, California has been at the forefront of creating a physical capital of electrical vehicles that minimizes emissions through programs that include zero emission electric buses, on-demand electric shuttles, and numerous charging depots. In Detroit, riddled with underinvestment for its transportation infrastructure through the years, proposed eclectic solutions (in the new strategic transportation plan) to introduce multimodal aspect of car and bike sharing, and partnership with transit agencies to promote public transportation. Florida is addressing sustainable transportation by testing autonomous electric shuttles, free of charge to the residents to encourage public transport usage (Sisson, 2018).

Additionally, some cities have demonstrated the use of low-environmental impact transportation modes with enhanced accessibility. Washington DC implemented a Metrobus system on 338 routes and 485 buses using natural gas instead of fossil fuels, complemented by the shared bike system. New York and New Jersey deployed the PATH train and encouraged biking and walking through the New Jersey Bicycle & Pedestrian Resource Center. The Santa Maria Area Transit (SMAT), Breeze bus, and the Clean Air Express have been sustainable modes of transportation connecting Santa Maria and Santa Barbara in California (Taylor, 2018).

The developments in sustainable transportation have not been limited to the city level, but it has been implemented by various institutions such as universities to get their staff and students to use public transportation. Cornell University initiated a clean campus drive using “Big Red Bikes”, a free bike share program. University of Louisville implemented an incentive program for students where they can use public transport for two years and receive a $400 voucher to purchase a bike (EA, 2017).

2.2.5 Sustainability Measurement and Rating Systems

In order to properly implement true sustainable transportation systems, there has been a need to accurately quantify sustainability in a standardized manner to enable a logical comparison between various alternatives for any project. Bueno et al. (2015) emphasized the need for standardization of sustainability assessment and identified decision-making techniques (MCDA, LCA, CBA), rating systems (ENVISION, CEEQUAL), and model frameworks for its assessment. They critiqued the decision-making models such as cost-benefit analysis (CBA), multi-criteria decision analysis (MCDA), and life cycle analysis (LCA) for not being able to incorporate the social, economic, and environmental (also known as the triple bottom line) aspects of sustainability. Furthermore, the authors identified the inability to perform projects’ comparison and tradeoff analysis as a significant drawback of model frameworks. Rating systems on the other hand “provide guidance and constitute a good basis for integrating sustainability over the whole life cycle of infrastructure projects, from planning through operation and maintenance” (Bueno et al., 2015). Therefore, rating systems have been chosen as the preferred method of sustainability assessment, and there have been several major transportation sustainability rating systems such as the systems discussed below.

2.2.5.1 STEED

The Sustainable Transportation Engineering and Environment Design (STEED) was developed as a self-evaluation tool by H.W. Lochner based in Chicago, US in 2008. This rating system aimed at quantifying the sustainability through a set of seven credits (totaling to 153 points) in each of social, economic, and environmental (triple bottom line) for the planning, environmental assessment, design, and construction phases of a transportation project (Abdul, 2012). Even though this system quantifies the sustainability of transportation projects it "does not provide any certification" (Abdul, 2012).

2.2.5.2 Greenroads

The Greenroads rating system was developed in the US by University of Washington and CH2M HILL in 2009 for road projects in design and construction phases (Muench et al., 2009). The major focus of this rating system pertains to design concerns regarding choice of materials, and even though equity and access of the transportation system has been addressed, it is majorly "oriented towards environmental aspects" (Bueno et al., 2015). The system consisted of required and voluntary criteria. The "required criteria" were divided into energy and carbon footprint, low impact development, social impact analysis, community engagement, life cycle costs, quality control, pollution prevention, waste management, noise and glare control, utility conflict analysis, and asset management while the "voluntary criteria" were divided into environment and water, construction activities, material and design, utilities and control, access and livability, and creativity and effort (Mehany, 2016).

2.2.5.3 GreenLITES

The Green Leadership in Transportation Environmental Sustainability (GreenLITES) was developed in the US by New York State DOT in 2010 as a self-certification program primarily for highways (NYSDOT, 2010). The major motivation behind this project was to "improve the quality of transportation infrastructure that minimize environmental impacts". Furthermore, it provides a platform for assessment of various design alternatives and award a unique level of sustainability (NYSDOT, 2010). The system has five major quantification criteria comprising sustainable sites, water quality, material and resources, energy and atmosphere, and innovation. Gudmundsson et al. (2016) suggested changing the GreenLITES system's expectations and revise its scope to accommodate more projects as this certification system directs its efforts majorly on preservation. Additionally this system has been majorly developed for internal use by NYSDOT (Abdul, 2012).

2.2.5.4 BE²ST

Building Environmentally and Economically Sustainable Transportation-Infrastructure-Highways (BEST) rating system was developed in the US (in 2008) by the recycled materials resource center at University of Wisconsin. This system aims to provide greater sustainability by assessing alternatives in the planning stages using life cycle assessment (LCA) and life cycle cost analysis (LCCA) while varying the alternatives' weights through an analytical hierarchical process (AHP). Equipped with a dual layer of assessment, it screens the alternatives based on existing regulations and assess the level of sustainability using environmental and economic indicators (Lee et al., 2011). It consists of nine criteria – Greenhouse gas emissions (GHGs), energy use, waste reduction including ex-situ materials, waste reduction including in-situ materials, water consumption, social carbon cost saving, life cycle cost (LCC), traffic noise, and hazardous waste (Lee et al., 2011; Mehany, 2016). Even though this system uses different methods to quantify the sustainability of transportation projects, it fails to provide a diverse metric for assessment of a few other sustainable aspects (such as quality of life).

2.2.5.5 STARS

The Sustainable Transportation Analysis and Rating System (STAR) was developed in 2012 by collaborative efforts of numerous entities, led by the Sustainable Transportation Council (SRT), Portland Bureau of Transportation, and the Santa Cruz County Regional Transportation Commission (Mehany, 2016; TRB, 2011). This rating system provides the stakeholders with a life cycle assessment of surface transportation projects for an enhanced decision-making (STC, 2012). Contrary to other rating systems, STARS focusses on system planning operations and maintenance of a project where project stakeholders are allowed to set their own goals and objectives for personalized assessment (Dondero et al., 2013). Since this rating system allows the stakeholders to set their goals and objectives, it has been difficult to make an equitable comparison between various projects due to the different definitions for sustainability.

2.2.5.6 I-Last

The Illinois Livable and Sustainable Transportation (I-LAST) was developed in 2012 through a collaboration between Illinois Department of Transportation (IDOT), the American Council of Engineering Companies (ACEC), and the Illinois Road and Transportation Builders (IRTBA). This rating system aims to "provide a comprehensive list of practices that bring sustainable results for highway projects" (IDOT, 2012). It consists of eight categories namely planning, design, environmental, water quality, transportation, lighting, materials, and innovation (Mehany, 2016). One of the drawbacks of using this system is the inability to adequately cover the triple bottom line (TBL) in sustainability assessment as it majorly focuses on environmental criteria. Furthermore, the usage of this system has been "advisory" and its development has been left to the industry leaders which can make it biased (Bueno et al., 2015; IDOT, 2012). Biased views could come from the limited experience of industry professionals or the urge to compare transportation projects, and showcase "being a champion" in the area of sustainability.

2.2.5.7 INVEST

The Infrastructure Voluntary Evaluation Sustainability Tool (INVEST) was developed in 2012 as a web-based self-evaluation tool by the Federal Highway Administration (FHWA) to encompass the entire life cycle of projects. This rating system aims for a project to go above and beyond while trying to maximize the sustainability (FHWA, 2012). The latest version of INVEST divides the system into four modules namely system planning for states (includes 16 criteria), system planning for regions (includes 16 criteria), project development (includes 33 criteria), operations and maintenance (includes 14 criteria). Even though this system is very comprehensive, it fails to address all other transportation systems (other than highways) (FHWA, 2012). Additionally, according to Oluwalaiye and Ozbek (2019), this rating system does not address the climate threats due to the project, signifying that it omits the resilience aspect of transportation projects.

2.2.5.8 CEEQUAL

The Civil Engineering Environmental Quality Assessment and Award Scheme Manual (CEEQUAL) was developed by the Institute of Civil Engineers (ICE) and the UK Government in 2003 (EAUC, 2007; Mehany, 2016). This rating system aims to equip the UK government with the necessary framework and assessment tools to improve the environment quality of projects in the planning, design, construction, and operation phases. It was majorly created to assess heavy civil projects such as bridges, public realm, rail, river, coastal defense, roads, and water supply (EAUC, 2007). Various categories defined in this rating system are (1) project strategy, (2) project management, (3) people and communities, (4) land use and landscape, (5) historic environment, (6) ecology and biodiversity, (7) water environment, (8) physical resources, and (9) transport (Mehany, 2016).

2.2.5.9 AGIC IS

The Australian Green Infrastructure Council (AGIC) developed the Infrastructure Sustainability (IS) rating system in 2012 to assess the infrastructure sustainability through design, construction and operations phases. This rating system assess a quadruple bottom line (environmental, social, economic, and governance) of infrastructure projects by "fostering efficiency, reducing waste, and lowering costs" (ARUP, 2012; ISCA, 2019). Unlike the above discussed rating systems, IS covers a plethora of infrastructure projects such as transport (roads, bridges, bike paths, sidewalks, ports, airports, railways), communication (communication transmission and distribution), water (water storage and supply, sewerage and drainage), and energy (energy transmission and distribution). This rating system is categorized into six major categories (1) management and governance, (2) using resources, (3) emissions, pollution and waste, (4) ecology, (5) people and place, (6) innovation (AGIC, 2012). One of the biggest limitations of IS rating system is unavailability of a self-assessment tool and AGIC states that "the use of the IS rating tool without formal certification does not entitle the user or any other party to promote the IS rating achieved" (AGIC, 2012).

2.2.5.10 ENVISION

ENVISION was developed as a coordinated effort between the Zofnass Program for Sustainable Infrastructure at Harvard University and the Institute for Sustainable Infrastructure (ISI) in 2012. This rating system aims to provide an assessment of triple bottom line of sustainability during the planning, design, construction, operation and maintenance, and end of life phases. It is the only rating system with components reflecting both sustainability and resilience. Furthermore, this is the one of the few comprehensive systems that can be used for all infrastructure systems such as energy (distribution, hydroelectric, coal, natural gas, wind, solar, biomass), water (treatment, distribution, storage, stormwater, flood control, nutrient management), waste (solid waste, recycling, hazardous waste, collection and transfer), transportation (airports, roads and highways, bike paths, railways, transit, ports, waterways), landscape (public realm, parks, ecosystem services, natural infrastructure, environmental remediation), and information (telecom, cables, internet, phones, data centers, sensors). ENVISION has been divided into six categories (1) quality of life (QL), (2) leadership (LD), (3) resource allocation (RA), (4) natural world (NW), and (5) climate and resilience (CR), each having indicators known as "credits" (total of 64 credits in the system). A detailed list of credits and associated level of achievement has been mentioned in Table 1.

Table 1: ENVISION credits

Credits	Improved	Enhanced	Superior	Conserving	Restorative
QL1.1 Improve Community Quality of Life	2	5	10	20	26
QL1.2 Enhance public health and safety	2	7	12	16	20
QL1.3 Improve construction safety	2	5	10	14	
QL1.4 Minimize noise and vibration	1	3	6	10	12
QL1.5 Minimize light pollution	1	3	6	10	12

QL1.6 Minimize construction impacts	1	2	4	8	
QL2.1 Improve community mobility	1	3	7	11	14
QL2.2 Encourage sustainable transportation		5	8	12	16
QL2.3 Improve access and wayfinding	1	5	9	14	
QL3.1 Advance equity and social justice	3	6	10	14	18
QL3.2 Preserve historic and cultural resources		2	7	12	18
QL3.3 Enhance public views and local character	1	3	7	11	14
QL3.4 Enhance public space and amenities	1	3	7	11	14
LD1.1 Provide effective leadership and commitment	2	5	12	18	
LD1.2 Foster collaboration and teamwork	2	5	12	18	
LD1.3 Provide for stakeholder involvement	3	6	9	14	18
LD1.4 Pursue byproduct synergies	3	6	12	14	18
LD2.1 Establish a sustainability management plan	4	7	12	18	
LD2.2 Plan for sustainable communities	4	6	9	12	16

LD2.3 Plan for long-term monitoring and maintenance	2	5	8	12	
LD2.4 Plan for end-of-life	2	5	8	14	
LD3.1 Stimulate economic prosperity and development	3	6	12	20	
LD3.2 Develop local skills and capabilities	2	4	8	12	16
LD3.3 Conduct a life-cycle economic evaluation	5	7	10	12	14
RA1.1 Support sustainable procurement practices	3	6	9	12	
RA1.2 Use recycled materials	4	6	9	16	
RA1.3 Reduce operational waste	4	7	10	14	
RA1.4 Reduce construction waste	4	7	10	16	
RA1.5 Balance earthwork on site	2	4	6	8	
RA2.1 Reduce operational energy consumption	6	12	18	26	
RA2.2 Reduce construction energy consumption	1	4	8	12	
RA2.3 Use renewable energy	5	10	15	20	24
RA2.4 Commission and monitor energy systems	3	6	12	14	
RA3.1 Preserve water resources	3	5	7	9	12
RA3.2 Reduce operational water consumption	4	9	13	17	22

RA3.3 Reduce construction water consumption	1	3	5	8	
RA3.4 Monitor water systems	1	3	6	12	
NW1.1 Preserve sites of high ecological value	2	6	12	16	22
NW1.2 Provide wetland and surface water buffers	2	5	10	16	20
NW1.3 Preserve prime farmland		2	8	12	16
NW1.4 Preserve undeveloped land	3	8	12	18	24
NW2.1 Reclaim brownfields	11	13	16	19	22
NW2.2 Manage stormwater	2	4	9	17	24
NW2.3 Reduce pesticide and fertilizer impacts	1	2	5	9	12
NW2.4 Protect surface and groundwater quality	2	5	9	14	20
NW3.1 Enhance functional habitats	2	5	9	15	18
NW3.2 Enhance wetland and surface water functions	3	7	12	18	20
NW3.3 Maintain floodplain functions	1	3	7	11	14
NW3.4 Control invasive species	1	2	6	9	12
NW3.5 Protect soil health		3	4	6	8
CR1.1 Reduce net embodied carbon	5	10	15	20	
CR1.2 Reduce greenhouse gas emissions	8	13	18	22	26
CR1.3 Reduce air pollutant emissions	2	4	9	14	18

Achieving a unique level of achievement for each of the above credits requires a certain investment that can potentially lead to a higher social, economic, or environmental sustainability. Similar to sustainability, transportation systems' resilience is essential in maximizing the performance while resisting future natural hazards or system failures.

2.3 Resilience

The earliest definition of resilience is observed in the field of ecology wherein Holling (1973) identified resilience to be a "measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables". Later, resilience was defined in the field of psychology by Masten et al. (1990), as the "process of, capacity for, or outcome of successful adaptation despite challenging or threatening circumstances". Recovery and reconstruction costs between late 1980s to late 1990s for major natural disasters totaled to $87.8 billion and therefore, resilience for infrastructure became an integral part of nation's policy (FEMA, 2000b). FEMA (2000a) devised community-based disaster preparedness programs to enhance hazard mitigation measures to minimize the long-term risk to the society. Bruneau et al. (2003) defined resilience as the hazard mitigation ability of social units, ability to isolate the hazard impacts, and usage of strategies to minimize social disruption. Haimes et al. (2008) provided one of the earlier definitions of infrastructure resilience as being able to withstand significant disruptions within acceptable functionality loss parameters and recover within a minimum time threshold and within budget. Resilience has been also defined as system's ability to resist, absorb, accommodate, and recover from a disaster and restoration of basic functions of a system (Gallego-Lopez & Essex, 2016; UNISDR, 2009). These definitions were the first to incorporate a system perspective while thinking of resilience (Haimes et al., 2008; UNISDR, 2009). Berkeley et al. (2010) defined infrastructure resilience as the ability to reduce the magnitude and/or duration of disruptive events. Its effectiveness is dependent on participation, absorption, adaptation, and recovery from a potentially disruptive event". According to U.S. Presidential Policy Directive 21 (2013), resilience has been defined as the "ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions". Hale and Heijer (2017) suggested resilience as being an important organizational characteristic that bypasses any hazards that pose a threat to its primary objectives. Resilience also refers to the system's capacity of responding and adapting to any disaster condition without loss of critical system functionality (Systems Innovation, 2019). It should be observed from these definitions that resilience has been identified as the concept that addresses the pre-disaster, during disaster, and post-disaster phases. Often, the definitions fail to account for all the phases. The dimensions of resilience as described next, will provide more clarity about the various hazard phases and associated resilience dimension.

Resilience has been divided into four broad dimensions namely technical ("ability of physical system to perform to acceptable/desired levels when faced with hazards"), organizational ("capacity of organizations to manage critical facilities"), social ("measures designed to lessen the impact on communities"), and economic ("capacity to reduce both direct and indirect economic losses") (Bruneau et al., 2003). Another viewpoint categorized the dimensions as robustness (ability of system to withstand the impact of hazards), redundancy (ability of system to maintain function using substitutable components), resourcefulness ("capacity to identify problems, establish priorities, and mobilize resources"), and rapidity ("capacity to achieve goals under allocated time to contain losses and avoid future disruption") (MCEER, 2005). Consistently, Haimes et al. (2008) characterized resilience into redundancy and robustness. Ta et al. (2009) defined six properties of resilience namely, redundancy (availability of more than one resource to provide the same system function), autonomy of components (parts of system that can operate independently), collaboration (engagement of stakeholders and users to promote interaction, share ideas etc.), efficiency (optimization of input against output), adaptability (system flexibilities and capacity to learn from past experiences), and interdependencies (interconnectivity between different components of a system). Later, Berkeley et al. (2010) conceived resilience as a combination of robustness (ability to keep operating during hazard events), resourcefulness (ability to skillfully manage a disaster), rapid recovery (capacity to get back to normal as quickly as possible), and adaptability (absorption of lessons learnt. Taking inspiration from Bruneau et al. (2003), Rochas et al. (2015) divided resilience into organizational resilience (recognizing organizational interdependencies), economic resilience (depends on market and supplier access and jobs), community resilience (ability to plan and use resources and create networks between crucial components), socioeconomic resilience (integration of humans with ecosystems). Mehany (2016) identified adaptability, robustness, recovery, resourcefulness, recovery, and robustness as the components of infrastructure resilience. Shin et al. (2018) observed an inconsistency in defining the dimensions of resilience after a comprehensive review of previous literature. They described a resilient system to be robust, absorptive, restorative, and adaptive. Numerous research studies have been completed to address resilience quantification in addition to definition of various dimensions of resilience.

Hashimoto et al. (1982) presented novel research that suggested vulnerability and reliability quantification was necessary to understand the needed level of resilience. They observed a similar decreasing trend for both resilience and reliability with respect to the loss function (β denotes the loss function exponent) as shown in Figure 2.

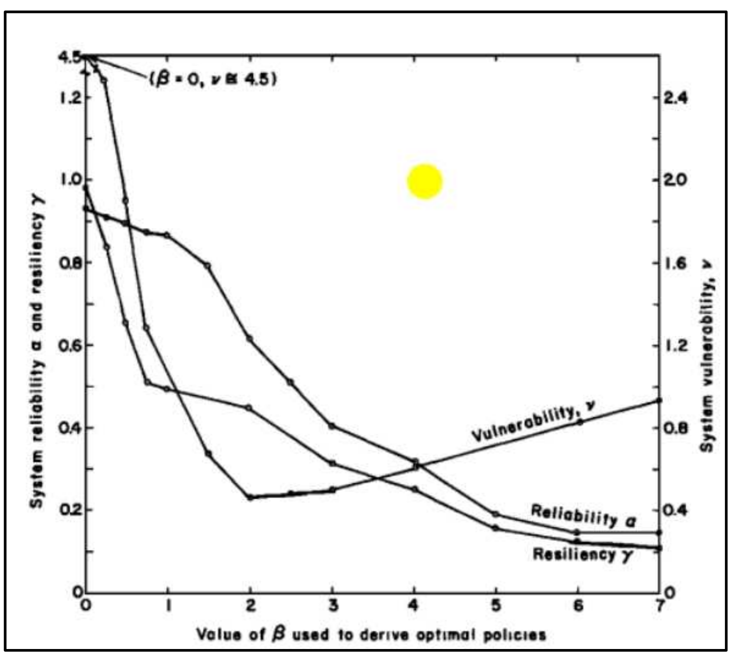

Figure 2: Dependence of vulnerability, reliability, and resilience (Hashimoto et al., 1982)

Haimes (2009) echoed the research by Hashimoto et al. (1982) and emphasized resilience as an important aspect to reduce the vulnerability due to different threats (or hazards). Vulnerability refers to adverse effects of threats to a system. United Nations Office of Outer Space Affairs (UNOOSA) posited that the loss of life and assets cumulatively determine the risk to a system due to a potential hazard (UNOOSA, 2019). Therefore, resilience has been suggested as a means to reduce risk and vulnerability (Haimes, 2009). Li and Lence (2007) used a probabilistic technique to quantify vulnerability, risk, and resilience, based on the performance function. However, they failed to show the interrelation between the three variables (vulnerability, risk, and resilience). Homeland Security Studies and Analysis Institute (2010) (HSI) explored the relation between risk and resilience by defining risk, vulnerability, and resilience clearly. Risk was defined as the product of threat, vulnerability, and consequences, each of them quantified as below-

$$Threat\ (P_a) = Probability\ of\ a\ hazard \qquad (1)$$

$$Vulnerability\ (1 - P_e) = Probability\ of\ hazard\ occurence\ within\ a\ specific\ time - period \qquad (2)$$

$$Consequences\ (C) =$$
$$Negative\ consequences\ in\ terms\ of\ dollar\ loss\ (human\ lives\ and\ economic\ losses) \qquad (3)$$

$$Risk = P_a \times (1 - P_e) \times C \qquad (4)$$

Resilience was stepwise quantified as per the popular bathtub function representation. HSI further developed a visual relation (shown in fig below) between risk-vulnerability and resilience-vulnerability using empirical values (Homeland Security Studies and Analysis Institute, 2010).

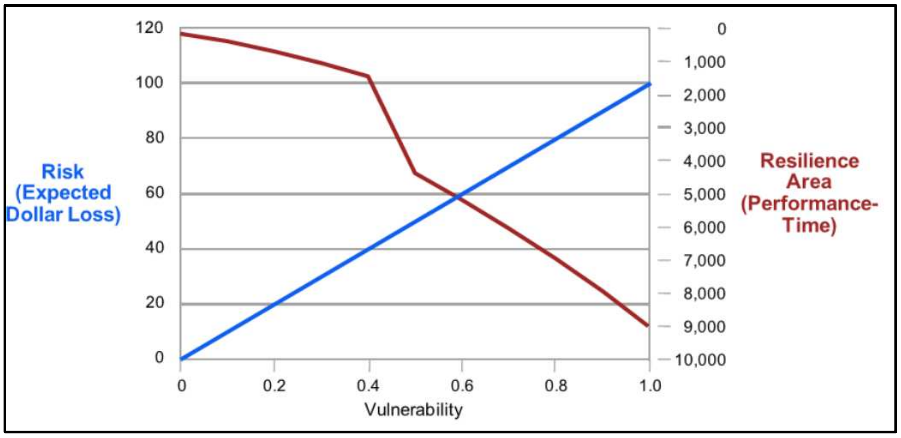

Figure 3: Dependence of vulnerability, risk, and resilience

As can be observed from Figure 3, risk linearly increases with increase in vulnerability while resilience non-linearly decreases with increase in vulnerability. The above tripartite relationship was simplified into a dual risk-resilience relation as represented in Figure 4.

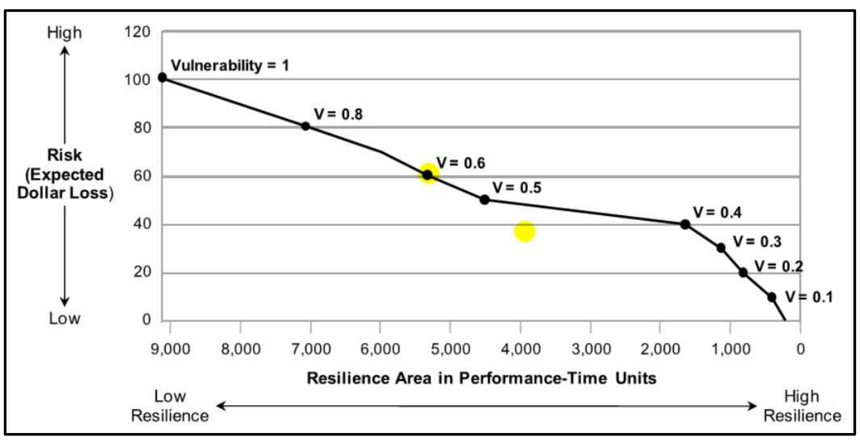

Figure 4: Risk and resilience curve

The above figure provides a granular view of risk and resilience relationship for specific vulnerability values. Though it shows an overall decreasing trend, there exists a non-linear relationship between risk and resilience.

Several other research studies quantified resilience without accounting for the relation between risk and vulnerability, but instead focused on system performance. Bruneau et al. (2003) defined the loss of resilience as the "size of degradation in quality over recovery time". In this research, resilience was represented by a quality function (represents system performance) versus time wherein quality started with an initial 100% and reduced significantly due to a shock, later regaining the lost quality during recovery.

$$R = \int_{t_0}^{t_1}[100 - Q(t)]dt \qquad (5)$$

In Equation (5), R represents resilience, Q(t) represents the quality of infrastructure at time t, and t_0 to t_1 represents the recovery time. This means that the resilience here is quantified as the area under the depression (popularly known as bathtub part of the performance function) created due to the reduction in performance in the performance vs time curve. Attoh-Okine et al. (2009) later modified the quantification of resilience as defined by Bruneau et al. (2003), to represent performance (measured as a percentage) of a system per unit time.

$$Resilience = \frac{\int_{t_0}^{t_1} Q(t)dt}{100(t_0 - t_1)} \qquad (6)$$

In Equation (6), Q(t) represents the quality (or performance) of infrastructure, t_0 represents the point in time before shock and t_1 is the point in time after shock. Haimes (2009) suggested the quantification of resilience depends on specific hazards, system recovery time, and associated investments. One of the first holistic resilience quantification came from Fisher et al. (2010) who combined the three dimensions of resilience (robustness, resourcefulness, and recovery) into one resilience index (equation below).

$$RI = \sum_{i=1}^{3} e_i \times V_i \qquad (7)$$

In Equation (7), RI represents the relative resilience index (ranging from 0 to 100), e_i represents the relative importance of robustness, resourcefulness, and recovery, and V_i represents the index value of each of the three dimensions (robustness, resourcefulness, and recovery). This quantification is consistent with the resilience definition; however, it fails to account for the adaptability portion of resilience.

Ouyang et al. (2012) followed a novel approach of dividing the performance versus time curve into three major stages signifying the resistant capacity (disaster prevention stage), absorptive capacity (damage propagation stage), and restorative capacity (recovery stage). According to them, the annual resilience was defined as the mean ratio between the area under the real performance curve and target performance curve.

$$AR = E\left[\frac{\int_0^T P(t)dt}{TP(t)\,dt}\right] = E\left[\frac{\int_0^T TP(t)dt - \sum_{n=1}^{N(T)} AIA_n(t_n)}{\int_0^T TP(t)dt}\right] \qquad (8)$$

In Equation (8), AR represents the annual resilience, E[] represents the expected value, T represents the time interval, P(t) denotes the actual performance curve, TP(t) is the target performance curve, n represents the event occurrence number, N(T) is the total number of event occurrences during time T, t_n is the occurrence time of nth event, and $AIA_n(t_n)$ represents the area between actual and target performance curves. Furthermore, Ouyang et al. (2012) defined resilience under multiple hazards by representing the real performance as a function of impact areas exposed to multiple hazards represented as a Poisson process.

$$E\left[\frac{1}{T}\sum_{n=1}^{N(T)} AIA_n(t_n)\right] = \sum_{h=1}^{H} \lambda^h E[AIA^h] + \sum_{h=1}^{H-1}\sum_{i=H+1}^{H} \lambda^{hi} E\left[AIA^{hi}\right] + \sum_{h=1}^{H-2}\sum_{i=h+1}^{H-1}\sum_{j=i+1}^{H} \lambda^{hij} E\left[AIA^{hij}\right] \qquad (9)$$

In Equation (9), nu represent the mean occurrence rate of hazard h, lambda represents the mean occurrence rate without considering co-occurrence of hazards, h, i, j, and k are hazard types, and E[AIA] represents the expected impact areas under hazard types. This research effort to quantify resilience is unique as it captures the uncertainty and represents the variables as a probability distribution function (Ouyang et al., 2012).

Francis and Bekera (2014) explained how risk dimension connect to the resilience of a system. They posited about risk having a tripartite relationship between hazard (events of concern), exposure (conjunction of properties of the process generating the hazard), and vulnerability (joint conditional probability distribution of system failure and event consequences given that an adverse event has occurred). They represented resilience as a relativistic factor between the post- and pre-disaster performance level, weighted as per the recovery speed, ensuring a quantitative representation of each leg of the system performance versus time graph. It can be observed that this idea is similar to the quantification idea presented by Ouyang et al. (2012) as both research define resilience as a ratio between actual and initial performance levels. Francis and Bekera (2014) defined resilience as in the below equation.

$$\rho\left(S_p, F_r, F_d, F_o\right) = S_p \frac{F_r}{F_o}\frac{F_d}{F_o} \qquad (10)$$

$$where\ S_p = \begin{Bmatrix} \left({}^{t_\delta}/_{t_r^*}\right) exp[-\alpha(t_r - t_r^*)]\ \ for\ t_r \geq t_r^* \\ \left({}^{t_\delta}/_{t_r^*}\right)\ \ otherwise \end{Bmatrix} \ (11)$$

In Equation (10) and (11), ρ_i represents the resilience factor, S_p is the speed recovery factor, F_o is the original stable system performance, F_d represents the performance level just after disruption, F_r* is the performance level after post-disruption equilibrium, F_r is the performance at stable level after recovery, t_δ is the slack time, t_r is the final recovery time, t_r* is the initial recovery time, and α is a parameter representing resilience decay.

Ayyub (2014) studied multiple resilience models in previous studies and developed a unique way of representing failure and recovery functions. Deviating from the common belief of failure being brittle, the authors suggested multiple paths of failure with several options of recovery, thereby defining resilience as

$$Resilience\ (R_e) = \frac{T_i + F\Delta T_f + R\Delta T_r}{T_i + \Delta T_f + \Delta T_r} \qquad (12)$$

In Equation (12), R_e represents resilience, T_i is the instance of failure, ΔT_f represents failure duration, ΔT_r represents recovery duration, ΔT_d represents the total disruption duration, F is the failure, and R is the recovery.

Berkeley et al. (2010) defined the four dimensions of resilience as representations of four different timelines in the system lifecycle. They represented robustness as a prior-to-event dimension, resourcefulness as during-an-event dimension, recovery as after-an-event dimension, and adaptability as lessons learnt post-event dimension.

2.3.1 Robustness

Robustness is the "ability of elements, systems or other units of analysis to withstand a given level of stress, or demand without suffering degradation or loss of function" (Bruneau et al., 2003). Multiple definitions of robustness were studied and categorized by Faber et al. (2006), in areas of structural analysis, software engineering, product development, ecosystems, control theory, statistics, design optimization, and decision making. They posited that robustness relates to specific hazard and system characteristics and defined it as the "degree to which the system performance characteristics are affected by specific hazards". Haimes (2009) defined robustness as the degree of insensitivity of a system to disturbances due to various hazards. Simply defined, robustness displays the property of a system that determines the power to withstand specific hazards (Francis & Bekera, 2014).

Working in the field of psychology, Walsh et al. (2013) quantified robustness as the product of probability of hazard occurrence and system functionality (can also be referred to as system performance).

$$Robustness = \int Functionality(x).Probability(x)\,dx \qquad (13)$$

Robustness was defined in civil engineering as the percentage of direct risk with respect to the total risk to the system, where the risk quantification was defined by taking a product of probability of disaster occurrence and its consequences (Faber et al., 2006).

$$I_R = \frac{R_{Dir}}{R_{Dir}+R_{Indir}} \qquad (14)$$

$$R_{Dir} = \iint_{x\,y} C_{Dir} P(\bar{F}|D = y)P(D = y|EX_{BD} = x) \times P(EX_{BD} = x)dydx \qquad (15)$$

$$R_{Indir} = \iint_{x\,y} C_{Indir} P(F|D = y) \times P(D = y|EX_{BD} = x)P(EX_{BD} = x)dydx \qquad (16)$$

In Equation (15) and (16), I_R is the robustness index, R_{Dir} represents the direct risk, R_{Indir} represents the indirect risk. Furthermore, EX_{BD} is the exposure level prior to damage, D refers to component damage, F is the system failure, C_{Dir} refers to the direct consequences, and C_{Ind} represents the indirect consequences.

Bruneau and Reinhorn (2007) defined robustness as the residual system performance level after the time to failure has been achieved as defined in Figure 5. Quantitatively this was represented as (B-C).

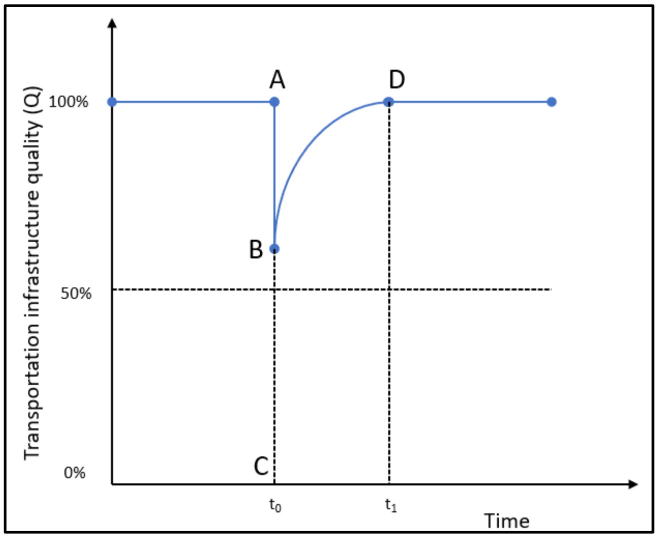

Figure 5: Resilience curve (adapted from (Bruneau & Reinhorn, 2007))

A similar idea of residual functionality was associated with robustness by Cimellaro et al. (2010). They quantified robustness as in the equation below, where L is the random variable for functionality decrease which has been expressed as a function of mean and standard deviation. This is conducive to the fact that various disasters can be represented by a unique probability distribution function, which is a representation of the random variable values. For example, the generalized extreme value (GEV) and generalized pareto distribution (GPD) distributions accurately represent the floods.

$$Robustness = 1 - \tilde{L}(m_L, \sigma_L); (\%) \qquad (17)$$

Ayyub (2014) detailed the idea by Bruneau and Reinhorn (2007) to include different failure rates and quantified robustness as a ratio between failure trend and system performance.

$$Failure(F) = \frac{\int_{t_i}^{t_f} f\,dt}{\int_{t_i}^{t_f} Q\,dt} \quad (18)$$

In Equation (18), F is the failure profile, f represents failure event(s), Q represents the system performance, t_i is the time of failure event occurrence, and t_f is the finish time of failure event. Inherently, this quantification embodies the core idea similar as the quantification by Faber et al. (2006).

2.3.2 Resourcefulness

Resourcefulness is defined as the "capacity to identify problems, establish priorities, and mobilize resources when condition exist that threaten to disrupt some element, system, or other unit of analysis" (Bruneau et al., 2003). They determined that human skills and improvisation are key to efficient resourcefulness. Berkeley et al. (2010) defined resourcefulness as the disruption management ability. According to Ayyub (2014), resourcefulness is the prioritize and diagnose problems while considering resource constraints. Zona et al. (2020) identified other dominant resourcefulness definitions in previous research – efficient preparation, response, and management of disruptive events (National Infrastructure Advisory Council, 2009); resourcefulness is people oriented rather than technology oriented compared to some other dimensions of resilience (like robustness), and includes scenarios' identification and prioritization to minimize damage and enhancement of information exchange and communication of decision making outcomes to community leaders and emergency response teams (Berkeley et al., 2010); resourcefulness encompasses resource usage optimization with respect to the time (Brown, 2015). Sharma and Chen (2020) elaborated the different between the resourcefulness in urban and rural areas, stating that urban areas have an abundance of trained personnel, vehicle support, safety transport, and use of technologies, hence reflecting a higher level of resourcefulness.

Fisher et al. (2010) identified seven sub-dimensions of resilience namely, training/exercises, awareness, protectiveness, stockpiles, response, new resources, and alternatives. Cimellaro et al. (2010) showed strong correlation between resourcefulness and redundancy ("capability to use alternative resources when the principal ones are either insufficient or missing"), further stating that redundancy is an important attribute that drives robustness and faster recovery. Cimellaro et al. (2010) also emphasized that resourcefulness is difficult to quantify as it majorly depends on human skills and improvisation during extreme event. Didier et al. (2018) quantified resourcefulness by expressing it as the capacity of resource mobilization.

While many researchers defined and quantified resourcefulness, Zona (2019) posited that resourcefulness can have a minimum value of 0 and highest value of infinity as it signifies the nature of a community which could be limitless. Zona et al. (2020) found a list of key performance indicators that drive resourcefulness which were categorized under political-economic, preparedness, trust, and creativity. A normalized weighting approach where the rating for each indicator was added to get the resourcefulness index.

$$RFS_{c.y} = \sum_{i=1}^{Q} x_{yj}.w_j \quad (19)$$

In Equation (19), RFS represents the resourcefulness index for region c in the year y, x represents the normalized index of several indicators, and w represents the weighting associated with indicators.

Unlike other researchers who defined equations for calculating resourcefulness, Sharma and Chen (2020) proposed that resilience be accounted as a constant exponential factor in recovery calculation. Furthermore, they posited that resourcefulness ranges from 0 to 1. While determining the criticality and susceptibility indices for prioritizing components in interdependent infrastructure networks, Balakrishnan and Zhang (2020) proposed using information regarding amount of resources required for restoration of various components of infrastructure.

2.3.3 Recovery

Bruneau et al. (2003) defined recovery as the "restoration of a specific system or set of systems to their normal level of performance". Alternatively, recovery has also been defied as the "capacity to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruptions" (Bruneau et al., 2003). This definition was modified and recovery was thereby characterized as the rapid return to original or improved operations and system reliability (Shinozuka et al., 2004). Berkeley et al. (2010) stated that a rapid recovery refers to return to normality after a disaster by efficiently using emergency pans, emergency operations, and human resources. Cimellaro et al. (2010) defined the recovery duration as the time required to restore desired functionality (same or better than original functionality). Gay and Sinha (2013) defined recovery as the "measures required to recover pre-disruption performance level in the system". Recovery has also been considered as a state of equilibrium after the event, whether to the initial state of the system or a changed state (Westrum, 2017).

One of the first significant contributions in quantifying recovery was undertaken by Hashimoto et al. (1982) who defined it as a conditional probability of system achieving satisfying performance in recovery given that the system performance has failed (shown in equation below) (Shin et al., 2018).

$$R = \frac{P(S_t \epsilon F \text{ and } S_{t+1} \epsilon R)}{P(S_t \epsilon F)} = P(S_{t+1} \epsilon R | S_t \epsilon F) \qquad (20)$$

In Equation (20), R represents the recovery probability, S represents satisfactory state, (t+1) represents the time step at satisfactory state, F denotes failure, and t represents the time step at failure.

Attoh-Okine et al. (2009) quantified recovery as the difference between the performance levels of a fully functioning system and the system at failure, signified as (A-B) in Figure 5. They further suggested that recovery to a 100% pre-disaster performance can be insufficient and a higher-level performance should be achieved to account for community needs. Bruneau and Reinhorn (2007) observed that system recovery depends on the amount of available resources and unlimited resource availability would inform the recovery curve to asymptotically reach zero. Furthering this idea, Ouyang et al. (2012) quantified recovery simply by considering the amount of resources for recovery and represented it as a single value with an assumption that each damaged component only required one unit of resources for recovery. Cimellaro et al. (2010) represented rapidity (one of the components of recovery) as the differential of functionality with respect to time as shown in equation below.

$$Rapidity = \frac{dQ(t)}{dt}; for\ t_{0E} \leq t \leq t_{0E} + T_{RE} \qquad (21)$$

In Equation (21), Q(t) represents system functionality, t_{0E} is the time when event E occurs, and T_{RE} is the recovery time. This equation provides an instantaneous value for recovery, and it was modified to find the average estimation of recovery defined as a ratio of total losses and recovery time.

$$Rapidity = \frac{L}{T_{RE}}\ (average\ recovery\ rate\ in\ percentage\ per\ unit\ time) \qquad (22)$$

In Equation (22), L represents the loss in functionality, and T_{RE} is the recovery time.

Ayyub (2014) had a novel approach of defining recovery event as six different functions representing the performance level after recovery – (1) better than new, (2) as good as new, (3) better than old, (4) expedited recovery to as good as old, (5) as good as old, and (6) worse than old. Recovery was quantitatively shown as a ratio of recovery and performance level.

$$Recovery\ (R) = \frac{\int_{t_f}^{t_r} r\ dt}{\int_{t_f}^{t_r} Q\ dt} \qquad (23)$$

In Equation (23), r represents one of the six conditions defined above, Q is the system performance, t_f is the failure time, and t_r is the time at the instant of recovery.

Francis and Bekera (2014) quantified recovery through an exponential function as shown in equation below.

$$S_p = \begin{Bmatrix} \left({t_\delta}/{t_r^*}\right) exp[-\alpha(t_r - t_r^*)]\ \ for\ t_r \geq t_r^* \\ \left({t_\delta}/{t_r^*}\right)\ \ otherwise \end{Bmatrix} \qquad (24)$$

In Equation (24), Sp represents speedy recovery factor, t_δ is the slack time, t_r is the final recovery time, t_r* is the initial recovery time, and α is a parameter driving resilience decay. All the above functions signify that the recovery dimension has been quantified as the difference in performance levels after failure and after recovery. When this numerical value is divided by the time variable, it helps in quantification of rapidity. In simple terms, recovery helps in understanding the new performance level with respect to the performance at failure, while rapidity helps calculate the rate of performance change.

2.3.4 Adaptability

Ta et al. (2009) defined adaptability as "system flexibility and a capacity for learning from past experiences. Adaptability also means implementing the lessons learned from previous disasters by revising the existing plans and procedures, and introducing new tools and technologies (Berkeley et al., 2010). Therefore, adaptability includes lessons learned after a disaster that can be used to make an efficient system to withstand future disasters. Francis and Bekera (2014) suggested that adaptability of a system refers to modifications in the current standard of procedure to mitigate the negative impacts of various hazards. Hegger et al. (2016), while finding strategies to move forward from a disaster, defined adaptability as "the capacity to adapt and transform, e.g. by including learning processes in system design and management". Shin et al. (2018) emphasized that a system with high adaptability will have a high overall resilience in the long-term to future hazards. Magoni (2020), while promoting resilience thinking, stated that adaptability is the degree of dynamic conformation of a system to changing environment while being subjected to limited resources.

Perez-Palacin et al. (2014) divided adaptability into absolute adaptability service, relative adaptability service, and mean of absolute adaptability services. The absolute adaptability measures the number of used components for providing a service representing as a Boolean metric.

$$AAS \in N^n | \, AAS_i = |UC_i| \qquad (25)$$

In the Equation (25), AAS represents the absolute adaptability of a service i, and UC represents used components to deliver a service i. The relative adaptability measures the number of used components with respect to the number of components as shown in equation below.

$$RAS \in Q^n | \, RAS_i = \frac{|UC_i|}{|C_i|} \qquad (26)$$

In the Equation (26), RAS represents the relative adaptability of a service, UC represents used components to deliver a service i, and C represents total components offering service i.

The mean of absolute adaptability of services measures the mean number of use components per service provided.

$$MAAS \in Q | MAAS = \frac{\sum_{i=1}^{n} AAS_i}{n} \quad (27)$$

In Equation (27), MAAS represents the mean of absolute adaptability of services, and n represents total number of services. Though the above equations for adaptability for services have been created for software engineering systems, the concepts can be leveraged for application to transportation systems. Though this research effort was conducted in the area of electrical systems engineering, the concepts can certainly be applied to disaster adaptability for transportation systems.

Adaptability should be derived using the recovery path determined using a unique probability distribution (Fotouhi et al., 2017). Zhai et al. (2020) quantified adaptability as the arithmetic mean of per capita GDP, drainage network density in built-up areas, and green coverage rate in built-up areas.

The above sections detailed how resilience and its dimensions have been defined and quantified in previous research studies and it is imperative that there is a lack of consensus while defining and quantifying these variables which this research will address in the methodology section. It should be observed that various researchers have had differing opinions about the basic definitions of resilience and its dimensions, and their quantification. However, when these definitions and equations are observed from a holistic perspective, they seem to provide similar inferences. Still there remains points of differences in defining and quantifying these concepts, which this research addresses. The next section will discuss the importance of resilience and the benefits of creating a resilient transportation system.

2.3.5 Need for Resilient Transportation

Having discussed resilience concepts in previous sections, it is evident that all transportation systems need to be resilient amidst disaster events. Similar to familiar definitions of resilience, resilience of transportation systems has also been referred to as the ability "to recover and regain functionality after a major disruption" (Fletcher & Ekern, 2016). According to RA (2018), transportation resilience has been defined as the movement of people, goods, and services while withstanding hurdles to the functionality. The Federal Highway Authority Office of Operations has been pivotal in engaging the state Departments of Transportation (DOTs) to plan and design for resilience. There has been an innate need to consider existing conditions of transportation infrastructure and implement different measures to improve the operation and reliability in the face of an ever-changing climate. More importantly, transportation infrastructure is one of the most critical infrastructure systems as it is usually intertwined with other systems. For example, Winkelman (2015) determined that the telecom infrastructure is intertwined with the transport infrastructure and further noted that the resilience of transportation should protect the transport infrastructure itself, telecom infrastructure, and other interconnected infrastructure. Baylis et al. (2015) realized that an inability to assess resilience benefits can lead to selection of the least cost resilience strategy which can potentially incur more investments in the operation and maintenance phase and unmitigated failures during disastrous events. Devoid of resilience, the transportation networks can be negatively impacted in cities leading to slow emergency response, disruption of economy and trade, and stressed social well-being of citizens (Minaie & Miller, 2020). Minaie and Miller (2020) also focused on existing systems which fare below C grade as per the ASCE report card. These systems consisted of aging transportation systems which need severe upgrades in order to be more resilient towards impending hazards.

2.3.5.1 Benefits of Resilient Transportation

Transportation is linked to other infrastructure systems such as stormwater, telecom and therefore, investing in resilient transportation can co-benefit other infrastructure systems in a cost-effective manner. For instance, Iowa DOT adopted resilience strategies in transportation systems and projected a benefit of $6.6

million in avoided damages in other coexisting systems (Godschalk, 2003). Resilient transportation can help in decreasing the urban heat island, decreasing stormwater runoff, and increasing the flood resilience while maintaining the ecosystem services (Winkelman, 2015). Incorporating resilient strategies in transportation projects reduces the cost of repairs as the systems can sustain higher impacts during disaster events with minimal disruptions to sustain the public safety and cities' economy (Baylis et al., 2015). In their report, private agencies' participation was encouraged to offset the funding deficit from the federal government in creating resilient transportation systems. Demand for resilient transportation should come from the state which was evident in their recommendation 3.4 – "require state, local, and regional partners to conduct a simple resilience impact assessment as a prerequisite for receiving federal funding for major capital investment projects". For instance, the Metropolitan Transportation Commission (MTC) in San Francisco planned for earthquakes and performed several seismic retrofitting to protect the rail infrastructure. Transportation systems have been the cornerstone for socioeconomic development over their life cycle and its resiliency ensures the capitalization of those benefits. These benefits include but are not limited to reduced carbon emissions, reduced congestion, reduced traffic mortality, improved urbanization and land uses, better quality of life, new business opportunities, and development of the built environment (Kaewunruen et al., 2016). Several examples from around the globe and in the US helps in understanding the resilience strategies adopted in those projects.

2.3.5.2 Examples of Resilient Strategies in Transportation Globally

Serulle et al. (2011) conducted a case study in the Dominican Republic after the country experienced a devastating hurricane to provide possible solutions against future disasters. These proposed solutions included (1) improvement of infrastructure maintenance regulations to lower the probability of street blockages, (2) adding capacity/fluidness by addition of lanes to existing roads and highways to increase the mobility and route choices, thereby enhancing the performance characteristics, and (3) increasing the reliability of transportation system to encourage greater public usage. The World Bank Group (2019) has promoted transportation resilience in accordance with the Paris Climate Convention to ensure that these systems can withstand the impacts of climate change. Nationally determined contributions (NDCs) have been suggested as one of the primary ways to reduce carbon footprint while adopting resilient strategies and holding governments accountable to its implantation. Being susceptible to extreme weather events, Mozambique adopted a comprehensive transportation resilience approach by promoting road asset management while focusing on life cycle costing, building network resilience and identifying critical road sections, a similar approach to Colorado Department of transportation (CDOT)'s. This helped improve redundancy and thereby enhance climate resilience (World Bank Group, 2019). The design of seawalls constructed in the Rikuzentakata city in Iwate on the northwestern coast of Honshu, Japan, was integrated with the existing ecosystem. Roads were used as seawalls and 230 people were saved during the 2011 Tohoku earthquakes by an East Sendai Expressway which is about seven to ten meters high as it blocked the tsunami debris from the Pacific Ocean (Forni et al., 2018).

2.3.5.3 Examples of Resilient Strategies in Transportation the US

There are several examples on adopting resilience strategies in the U.S. In Colorado, Colorado DOT and FHWA measured asset criticality for the Colorado's I-70 corridor by taking a weighted average among seven different scales including the annual average daily traffic (AADT), the American Association of State highway and Transportation Officials (AASHTO), roadway classification, freight value per ton at the country level in millions of dollars per year, tourism dollars generated at the country level in millions of dollars per year, Social Vulnerability Index (SoVI) scores at the country level, and system redundancy measured by the CDOT's redundancy map (Weilant et al., 2019). In Washington state, the king county created a climate action plan to improve the adaptability of its transportation system using resilience strategies such as improving drain maintenance, adjusting travel routes, reducing travel frequency, forecasting repair cycles, and moving rolling stock to higher elevation. (Rosenzweig, 2013). Investing in resilient strategies such as retrofitting of portions of the infrastructure system, flood reduction pumps, and transportation hardening are essential, but it can only be incentivized through accommodating federal and statewide policies. Therefore, as part of state project planning, Rosenzweig (2013) advised incorporating climate risks in site selection for transportation projects, avoiding highly-vulnerable areas for roads and rail projects, and adopting land use to store rainwater and reduce windspeeds close to major roads. Accordingly, California Department of Transportation (Caltrans) has been strategically planning their transportation projects to adapt to coastal erosion and sea level rise by integrating environmental impact assessments. For example, a part of Highway 1 has been moved inland in the San Luis Obispo County due to sea level rise.

Through several examples and strategies of resilience application in transportation projects in the above sections, it is evident that resilience measurement is essential. Quantification of resilience and its dimensions have been discussed in previous sections. Similar to sustainability, since numerous projects are implementing resilient strategies, there is a need for standardized infrastructure resilience rating systems (another means of resilience quantification).

2.3.6 Resilience Measurement and Rating Systems

Rating systems are a great way of assessing infrastructure resilience in addition to, and through the incorporation of, equations, event probabilities, policies, and dedicated analytical models. These rating systems can be used for performance measurements, assessing system behavior, or making important design decisions (Croope & McNeil, 2011). Many of these rating systems are voluntary programs that encourage the decision makers and the community to participate in building a more resilient infrastructure (Carlson et al., 2012). Alessa et al. (2008) created a rating system for vulnerability assessment of water infrastructure by obtaining a consensus among experts that included anthropologists, ecologists, geomorphologists, hydrologists, sociologists, and water engineers. As infrastructure resilience rating systems is a developing area of research, only a few relevant studies can be found. Among the rating systems discussed in the sustainability section, only CEEQUAL, AGIC, and ENVISION directly address resilience.

2.3.6.1 CEEQUAL

The (CEEQUAL) rating system has one resilience category with three sub-categories – risk assessment and mitigation, flooding and surface water runoff, and future needs (CEEQUAL, 2019). Overall, this category considers proactive hazard identification, risk assessment, and mitigation in addition to designing for future needs. The “Risk assessment and mitigation” subcategory aims to perform risk assessment and mitigation due to different hazards (natural or man-made) over the design life of the system. The total points for this credit is calculated based on the number of points achieved in identifying resilience requirements, identifying dependencies, communicating dependencies, identifying and assessing risks, communicating risks, and formulating a resilience plan. The “Flooding and surface water runoff” subcategory aims to minimize the negative impacts of flooding through the following assessment criteria – (1) flood risk assessment, (2) flood risk-based enhancements, (3) sustainable drainage systems, (4) long-term flood resilience and adaptation, (5) implementation of flood risk-based enhancements, (6) implementation of sustainable drainage systems, and (7) managing run-off at source. Finally, the “Future needs” subcategory aims to improve the adaptability of infrastructure systems and minimize further disruptions due to a disaster event. It has a small assessment criterion comprising three dimensions namely, identifying future needs, opportunities to address future needs, and designing for future needs (CEEQUAL, 2019).

2.3.6.2 AGIC IS

The Australian Green Infrastructure Council’s (AGIC) Infrastructure Sustainability (IS) rating system has a resilience category with two sub-categories – resilience strategy and climate and natural hazard (ISCA, 2019). The “resilience strategy” subcategory has three levels of achievement with predetermined checklist for each, that provides specific number of points. This section helps identify the vulnerability of the asset and its served community to certain shocks (e.g., hazards) in addition to identifying its interdependencies with other assets. Addressing vulnerabilities is important and the majority of points are provided for community involvement into mitigating the vulnerabilities and creating a strong resilience plan. The “climate and natural hazard” subcategory also has three levels of achievement with a predetermined checklist providing a point for achieving each level. Level 1 addresses collection of data related to all potential hazards and calculation of risk related to each hazard to categorize those by high and low priority. An interdisciplinary team involvement is essential in the selection of the risk mitigation options. Level 2 addresses indirect risks to the system followed by their prioritization and involvement of government representatives in this process. Level 3 considers the benefit-cost ratio of mitigation options to select the optimal option and involves a comprehensive set of stakeholders (ISCA, 2020).

2.3.6.3 ENVISION

ENVISION rating system provides the most comprehensive explanation and breakdown as compared to other rating systems discussed above. This category aims to promote resilience and inform infrastructure regarding its resourcefulness, robustness, redundancy, flexibility, integration, and inclusivity. This category has been divided into six credits as shown in Table 2. CR 2.1 avoids development in hazard prone sites and assesses the degree to which the project is designed and sited to avoid the hazard vulnerabilities, thereby mitigating any site-related risks. CR 2.2 helps in developing a comprehensive climate change vulnerability assessment and quantifies it based on the scope and comprehensiveness of the vulnerability assessment plan. CR 2.3 conducts multi-hazard risk assessment and resilience evaluation, and it is quantified based on the level of comprehensiveness. CR 2.4 helps to support the increased project and community resilience through establishment of clear goals and objectives. It is assessed based on the degree of expansion of resilience goals and objectives from initial commitments to quantifiable project objectives, long-term operating plans, and community-wide development plans. CR 2.5 increases the resilience through increasing the life cycle performance, improving the ability to withstand hazards, and maximizing durability. It is assessed as the degree of incorporation of increased durability, robustness, and extension of useful life in the projects. Lastly, CR 2.6 helps in the enhancement of operational relationships and strengthening the functional integration of the project into interdependent infrastructure systems. This credit is assessed as a degree of integration with other infrastructure systems and the increase of resulting resilience.

Table 2: Envision resilience credits

Credits	**Improved**	**Enhanced**	**Superior**	**Conserving**	**Restorative**

CR2.1 Avoid Unsuitable Development	3	6	8	12	16
CR2.2 Assess Climate Change Vulnerability	8	14	18	20	-
CR2.3 Evaluate Risk and Resilience	11	18	24	26	-
CR2.4 Establish Resilience Goals and Strategies	-	8	14	20	-
CR2.5 Maximize Resilience	11	15	20	26	-
CR2.6 Improve Infrastructure Integration	2	5	9	13	18

Sustainability and resilience demand investments of both time and money, thereby opening dimensions of exploration of both the project duration and life cycle cost.

An analysis of the infrastructure rating systems (specifically transportation) shows significant improvements since the year 2000. Observing the dimensions of sustainability and resilience, however, present opportunities for improvement in the industry, particularly in the resilience domain. In addition, there are additional opportunities for improvement in areas such as integration between infrastructure systems, community and stakeholder engagement, and long-term monitoring, maintenance and data sharing across infrastructure and infrastructure rating systems to support better decision-making and policy-development. ENVISION offers the greatest level of detail for the US when adopting sustainability and resilience for transportation projects. Therefore, it has been selected for this research.

2.4 Project Duration

Project duration is defined in the Project Management Body of Knowledge (PMBOK) as “The number of work periods (not including holidays or other non – working periods) required to complete an activity or other project elements” (PMBOK, 1996). A more comprehensive definition by Cleland and King (1983) took the projects' life cycle into account in calculating project duration, which encompassed the total duration of the project, from the design to the closeout phase including schedule delays' impacts.

2.4.1 Properties/challenges

A project duration can be divided into construction duration and contract duration. Construction duration represents the total number of working days excluding the weekends and holidays. On the contrary, contract duration elucidates the duration defined in the contract between the owner and the contractor including all the holidays and the weekends (Williams, 2008). The duration of a project usually changes due to external factors (i.e., unforeseen conditions) which could result in schedule overruns. The solution to manage schedule overruns is to find the underlying causes behind the delay and mitigate these causes to preserve the overall project duration (Ahmed et al., 2002). Assaf et al. (1995) found 56 factors causing project delays and grouped them into 8 categories as: 1) Materials, 2) Manpower, 3) Equipment, 4) Financing, 5) Environment, 6) Changes, 7) Government relations, 8) Contractual relationships, and 9) Scheduling and Controlling Techniques. Wambeke et al. (2011) defined 10 most frequent factors that cause project delays and increase project duration, the most prominent being delay in shop drawings from the engineers. Cost overruns are closely associated with schedule overruns, where the impact of schedule overrun directly affects the project cost (Kaliba et al., 2009).

2.4.2 Effect of sustainability on project duration

The design duration of a sustainable projects may increase due to numerous sustainability measures which can increase the decision making complexity (Contreras Casado & Zuniga, 2018) yet the construction duration can be significantly reduced by sourcing materials closer to the project site which can reduce the lead time for procurement(Build Abroad, 2017). However, many studies reported a construction duration increase in infrastructure projects when incorporating sustainable measures. This duration increase was attributed to installation of a robust stormwater detention centers with added bioswales and detention pond, and installing PV panels for renewable energy which resulted in a more complex electrical systems installation, among many other sustainable features. (Fortunato III et al., 2012). The idea of duration overruns in sustainable construction was further supported by Hwang et al. (2013) who found that sustainable projects used 8% more time than traditional projects and an average delay of 4.8% was seen in comparison to the as-planned schedules. Valentine (2018) proposed using building information modelling (BIM) heavily in the design phase to assess the sustainable design options, thus reducing the number of errors and uncertainties in the construction phase to reduce the project duration. Evidently, new technology and concepts are helping reduce the project duration for sustainable projects, but often their implementation is restricted due to the higher cost or unavailability of those products to the consumers.

2.4.3 Effect of resilience on project duration

Wilson (2000) suggested that resilience implementation requires scenario-based strategic-planning rather than traditional planning, thus leading to increase in the duration for modeling of those scenarios. Similarly, Schultz et al. (2019) suggested that implementing resilient strategies can increase the project duration. Predominantly, long-term solutions that improve the robustness of a system lead to a more time consuming planning during the programing and design phases. Hahn and Sawislak (2018) advocated for spending more time in the planning and design phase to create more resilient infrastructure that requires low maintenance, which can result in increased construction duration due to resilient strategies' implementation. However, they also inferred from their research that "investing in infrastructure resilience can be an expensive and time-intensive process, but it is a necessary one".

2.4.4 Effect of operation and maintenance on project duration

Resilience affects not just the construction duration but the operation and maintenance duration as well. Maintenance has been divided into preventive, corrective, and reactive depending on the frequency and the occurrence of maintenance activities. Preventive maintenance is a proactive approach wherein activities are pre-planned and executed on a regular basis to keep the infrastructure in good condition, corrective maintenance refers to replacement and repair of faulty components of a system, and reactive maintenance happens post-failure (SSWM, 2018). The World Economic Forum (2014) report categorized the maintenance into improvement of asset utilization, reduction in O&M costs, extension of asset life, reinvestments to extend the life cycle, ensuring funding continuity, and reforming governance. EPA (2018) devised a maintenance plan that included identification of staff resources for inspection and maintenance, identification of maintenance triggers, updating standard operating procedures, securing funding for maintenance, enlisting the help of volunteers, and procuring equipment. Furthermore, they developed several field guides and checklists for performing maintenance activities for various pieces of infrastructure. FHWA (2015) devised regular maintenance activities supplemented by vulnerability assessment information to enhance the decision-making investments and ensure that an infrastructure asset adapts to the changing conditions, hence improving the overall resilience. Naumann et al. (2011) noted that the maintenance costs were often neglected while making decisions on building infrastructure projects and further encouraged to consider the life cycle of a project instead of solely construction duration. Black & Veatch (2019) emphasized pre-planning of operations and maintenance activities of infrastructure and a higher upfront investment to minimize the number of scheduled maintenances. The resilience measures can be adopted in the planning phase of a project and these measures can be implemented in the construction phase. Resilience measures are also planned for to be implemented in the operations and maintenance phase. These measures can directly or indirectly impact the resilience of a transportation project (Schultz et al., 2019). While proactive planning helps maintaining the functionality of the asset, incorporating resilience strategies in the planning stages can have optimal impact on the duration of disaster occurrence.

2.4.5 Disaster duration, recovery, and their impacts

A discussion about disaster duration (both natural and man-made) is necessary before the duration of disaster recovery can be assessed. More than 60,000 deaths are caused by natural disasters every year, with floods, droughts, and earthquakes resulting in highest losses (Ritchie & Roser, 2019). A decade-wise comparison of annual deaths for every natural disaster as shown in Figure 6.

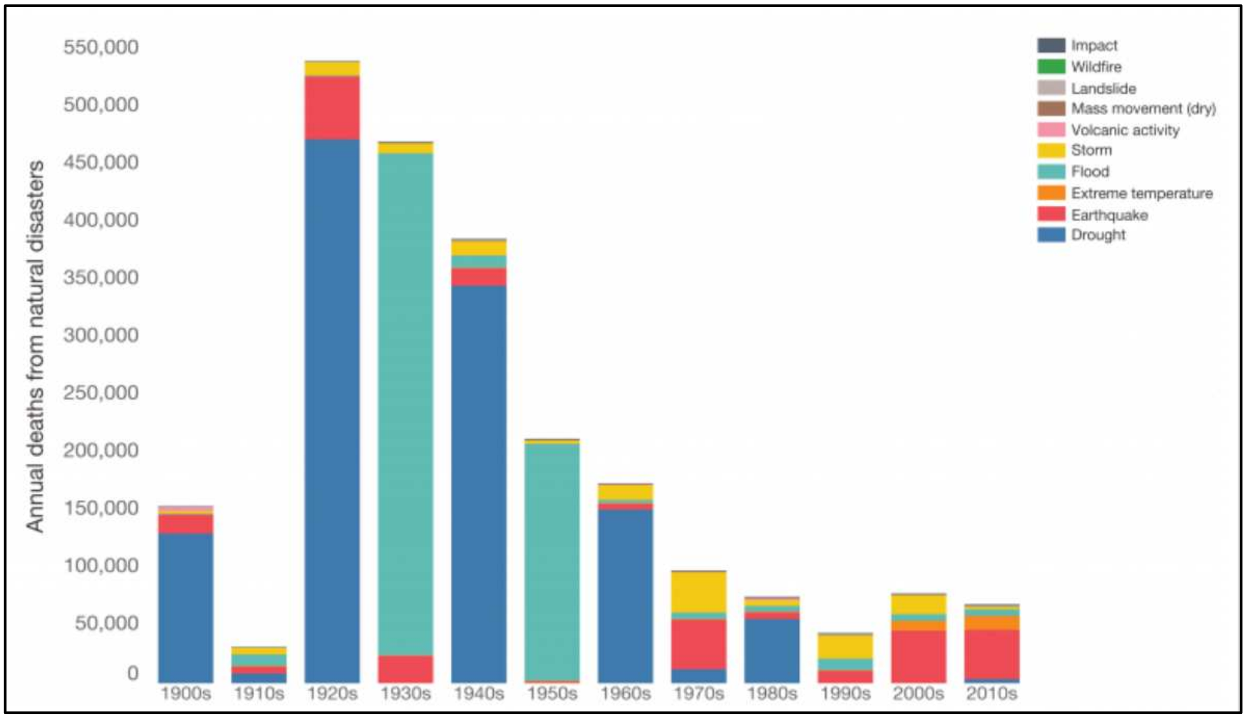

Figure 6: Global annual deaths from natural disasters

The World Health Organization (2002) categorized the disasters as natural and man-made, each of which was further broken down into sudden and progressive occurrences. An adaptation of their classification has been shown in Figure 7.

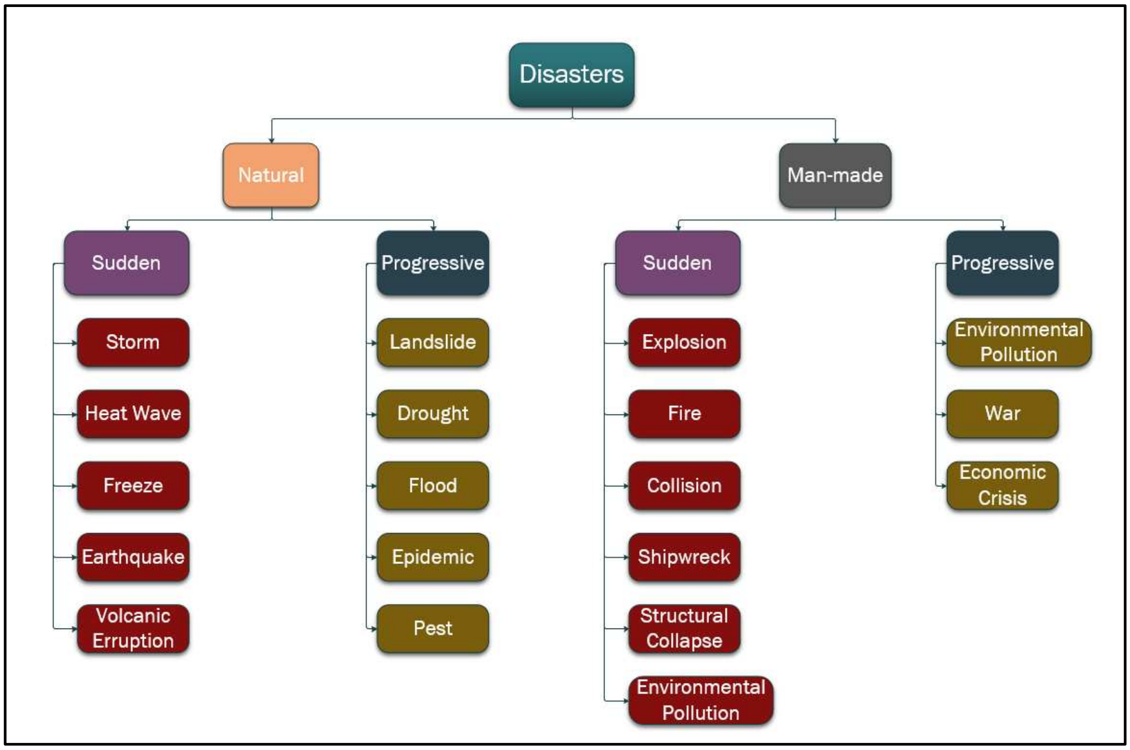

Figure 7: Types of disasters

Spiegel et al. (2007) assessed the 30 largest natural disasters, complex emergencies, and epidemics over a decade (from 1995 – 2004) to determine the average duration of each categorization. They defined natural disasters as an "acute onset of climatic hazards"; complex emergencies as "considerable breakdown of authority from external and internal factors" (can be considered progressive as per World Health Organization (2002)); and epidemics as "unusual increase in the number of cases of an acute infectious disease". Their analysis showed a median duration of one day for natural disasters, 365-14,965 days for complex emergencies, and 107 days for epidemics (Spiegel et al., 2007). Balasubramanian (2014) determined that disasters such as earthquakes, hailstorms, avalanches, and landslides have a sudden occurrence and classified progressive hazards in short duration hazards such as floods and hurricanes, and long-lasting duration hazards such as droughts. In an effort to determine the effects of disasters on mental health, the University of Rochester School of Medicine and Dentistry defined the length of several natural disasters – a few seconds for an earthquake or an explosion, hours or days for hurricanes and blizzards, and weeks for floods (URMC, 2018). Finally, the World Health Organization (2002) classified disasters' average duration as shown in Table 3.

Table 3: Average duration of disasters

Hazard Event	**Duration**	**Citation**
Natural - Sudden		
Storm	3 – 7 hours	(Thorp & Scott, 1982)
Heat Wave	1 – 3 days	(Smith et al., 2013)
Freeze	15 days	(NOAA, 2019)
Earthquake	10 – 30 seconds	(University of Utah, 2020)
Volcanic Eruption	7 weeks	(Simkin et al., 2001)
Natural - Progressive		
Landslide	10 mins – 35 days	(Guzzetti et al., 2008)
Drought	2 months	(Van Loon & Laaha, 2015)
Flood	9.5 days	(Dartmouth Flood Observatory, 2004)
Epidemic	10 weeks	(Fleming et al., 1999)
Pest		
Manmade - Sudden		
Explosion	Milliseconds	(FEMA, 2018)
Fire	52 days	(Kaufman, 2018)
Collision		
Shipwreck	30 mins – 1 hour	(Elinder & Erixson, 2012)
Structural Collapse	Few days	(NPDP, 2018)
Environmental Pollution		
Manmade - Progressive		

Environmental Pollution	5 years	(Almasy, 2010)
War	7 – 12 years	(Fisher, 2013)
Economic Crisis	17.5 months – 1.5 years	(Keng, 2018)

2.4.6 Duration of disaster recovery

Disaster recovery is mostly focused on getting a system back to original functionality, recovery of communities, recovery of businesses, and psychological recovery (Alhazmi & Malaiya, 2012; Chang, 2010; Picou, 2009). Full disaster recovery, especially when major infrastructure is damaged, can extend over a prolonged period of time such as the case Hurricane Katrina which took an initial three years for in New Orleans and a 10-year period for complete recovery Orabi et al. (2010).The duration of system functionality restoration is of the utmost importance since almost all other aspects of recovery is mostly dependent on it. Therefore, there have been a plethora of studies which focused on the system functionality recovery issues (duration, cost, time, etc.) using different means and methods. Chen and Huang (2006) studied post-earthquake scenarios using a neural network model with back propagation to predict recovery cost and duration. Orabi et al. (2010) proposed a resource utilization optimization model for infrastructure systems recovery which can optimally allocate resources to competing projects and minimize the duration and cost of recovery. This optimization model used three decision variables (project prioritization, contractor assignment, and overtime policy) to build a resource utilization model at the contractor level, project level, and activity level to create optimal recovery schedules that reflected the duration of disaster recovery. Croope and McNeil (2011) provided a graphical representation of time versus system performance and represented infrastructure resiliency in terms as a function of the post-disaster recovery duration, while suggesting that the new system performance post-recovery is always the same or less than the original performance. Contrary to this view, Ayyub (2014) suggested a novel approach to capture system recovery using six different recovery paths – "expeditious recovery to better than new (r1), expeditious recovery to as good as new (r2), expeditious recovery to better than old (r3), expeditious recovery to as good as old (r4), recovery to as good as old (r5), and recovery to worse than old (r6)". The time versus system performance charted in Figure 8.

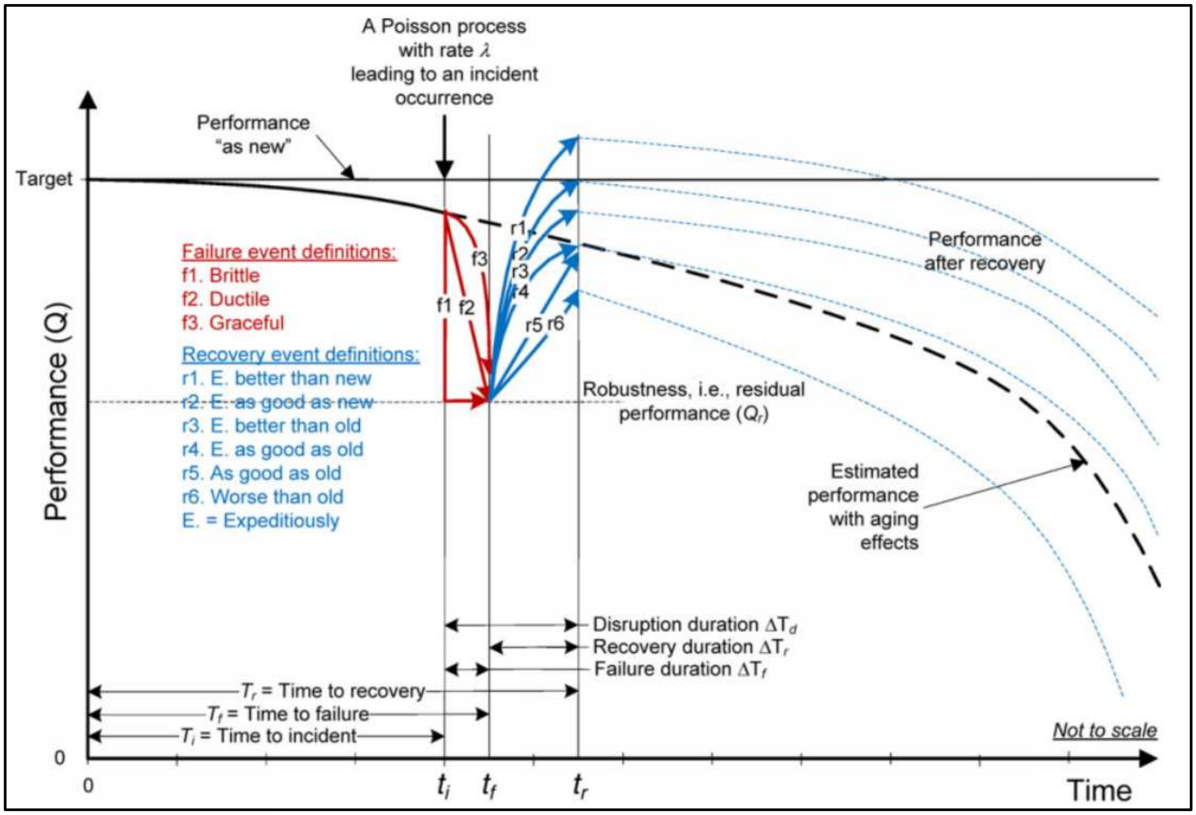

Figure 8: Recovery curves

Alhazmi and Malaiya (2012) suggested using cloud services such as usage of sensors to relay information faster to minimize the recovery time after a hazardous event and developing these practices into a disaster recovery plan. Freckleton et al. (2012) evaluated the resilience of transportation networks and their results implied that implementation of strong resilience strategies reduced the recovery time after disasters. Zhang et al. (2017) studied the post-disaster recovery for roads and bridges, and coined two important terms – total recovery time ("time required for the network to be restored to its pre-hazard functionality") and skew of the recovery trajectory ("captures the characteristics of the recovery trajectory that relates to the efficiency of those restoration strategies"). Zhang et al. (2017) reviewed multiple studies on disaster recovery and proposed four different trends for recovery strategies as shown in Figure 9.

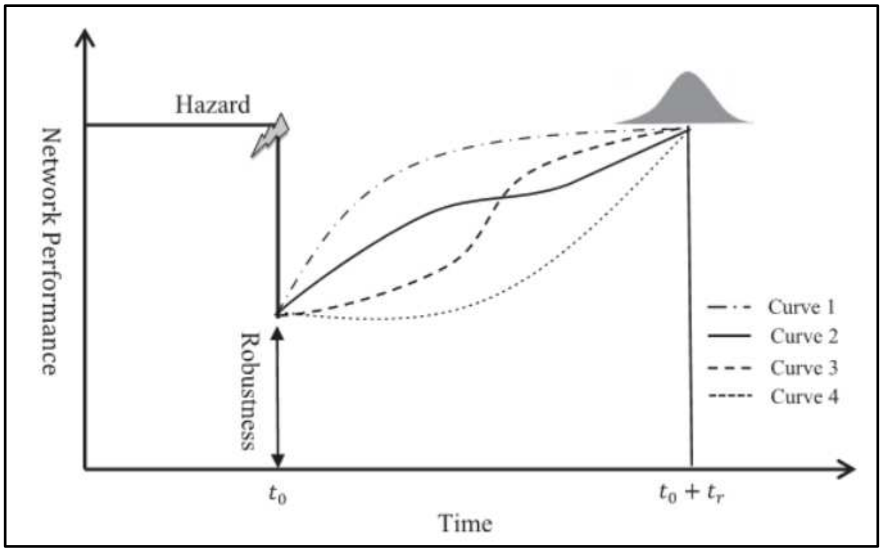

Figure 9: Recovery trends (Zhang et al., 2017)

They indicated that the prioritized recovery strategy selection will be curve 1, curve 2, curve 3, and curve 4 due to efficient early-stage recovery in curves 1 and 2, thus resulting in low service disruptions and minimal losses. Furthermore, they used this concept to optimize the system recovery schedule (Zhang et al., 2017). Qualitatively, Liu et al. (2016) defined several critical success factors to minimize the post disaster recovery duration and achieve rapid recovery: (1) establishment of recovery vehicle, (2) formulation of a flexible funding plan, community engagement, (3) selection of a rebuild driver, (4) determination of rebuild project prioritization methodology, and (5) standardization of data management mechanism. Numerous research studies pursued the dependence of stronger resilience on recovery times.

Resilient projects consider the project's life cycle from the planning and design phase, to the construction, operation, maintenance, and end of life phases (Environmental and Energy Study Institute, 2019). Therefore, the life cycle cost needs to be considered for the total cost of various life cycle phases.

2.5 Life Cycle Cost

Life cycle costing (LCC) has been defined as the summary of "all costs associated with the life cycle of a product/service/system that are directly covered by one or more of the actors of the life cycle (like supplier, consumer, end of life actors)" (Hunkeler et al., 2008). LCC is used to determine the "net present value

(NPV) of all relevant costs throughout the study period, including construction costs, maintenance and repair costs, replacement costs, energy cost, and residual costs" (Kneifel, 2010). Fuller (2010) defined LCC analysis as a method to assess the total cost of facility/system ownership as it accounts for acquisition cost, ownership cost, and disposal cost, and it can be used for project alternatives assessment to make sound design decisions. Furthermore, Fuller (2010) identified determination and quantification of economic effects of design changes as one of the biggest challenge to calculate the total LCC for various alternatives. Dwaikat and Ali (2018) reviewed multiple definitions for life cycle costing and elucidated that LCC is an appraisal technique to assess different investment alternatives by accounting for cost and savings associated with each investment alternative along a period of analysis. Salem et al. (2003) noted that most public funding decisions consider the initial cost instead of the life cycle cost which negatively impacts the decision making. Definition of a system boundary and functional unit is necessary when calculating the LCC.

2.5.1 System boundary and functional unit definition

Functional unit is the first step towards a life cycle approach to normalize the comparison of different alternatives (Turconi et al., 2013). Therefore, the functional unit helps compare different projects which may vary in size and an absolute value comparison may result in skewed results (Santero et al., 2011). A functional unit is the "amount, weight, and quality of the specific product or system being investigated" thus a road mile/kilometer can be used as the functional unit for calculating the road life cycle results, yet the entire road project can be considered as the functional unit for a practical comparison of different alternatives for the same project (QPC, 2019). (Mroueh et al., 2000). Huang et al. (2009) used 30,000 m^2 of asphalt to calculate the life cycle impact assessment of construction and maintenance phases of asphalt pavements. Huang et al. (2015) defined a meter of tunneling as the functional unit for conducting life cycle analysis of a Norwegian road tunnel project.

System boundary definition is important for any kind of life cycle assessment (impact assessment or cost assessment). The system boundary is determined by an iterative process wherein the significant components are chosen to be included in the system boundary after conducting a sensitivity analysis. In an LCA, system boundaries have been defined to include activities within the different unit processes that have significant consequences on the environment during the asset life cycle (Li et al., 2014). Three types of system boundaries have been defined by ECOIL (2015) – boundary between technological system and nature (raw material extraction and disposal phases), geographic area, time horizon, and boundaries between current and related life cycles. Anorga et al. (2019) defined multiple system boundaries which have been used in various research areas to determine the processes included in the life cycle study as in the following approaches:

1. Gate to Gate: refers to the life cycle of only the manufacturing process
2. Cradle to Gate: refers to the life cycle from raw materials extraction to manufacturing of the finished product (use phase and end of life phases are not included)
3. Cradle to Grave: This expands the boundary from the raw material extraction to the disposal of the product phase
4. Cradle to Cradle: It provides the most comprehensive life cycle study as it accounts for reuse and recycle after the end of life

Most researchers have used the cradle to grave approach in their life cycle studies. Flynn and Traver (2013) analyzed a rain garden considered a cradle to grave approach that included raw material extraction, manufacturing, transportation of materials to the site, construction, operation and maintenance, and disposal. Cradle to cradle approach has been inadequately addressed in previous infrastructure life cycle studies. However, due to the lack of data to conduct cradle to cradle study, and the scope of this research, the cradle to grave approach will be followed in calculating the LCC. After identifying the functional unit and setting the system boundaries, there are several parameters that are taken account to conduct an accurate LCC.

2.5.2 Parameters evaluated for conducting LCC

Fuller (2010) listed discount rate, cost period, and treatment of inflation as essential parameters to calculate the LCC. Discount rate has been used as the time normalization factor to make cost comparisons across different years by converting them to a present value. Discount rate has been calculated using the time value for money and the associated risks, in multiple studies (Tam et al., 2017). Discounting has also been the principle to illustrate that benefits and cost occurring sooner in time have a greater value as compared to the ones occurring later in time. In the US, buildings and infrastructure have different discount rates and each type of infrastructure will be discounted differently based on the Office of Management and Budget (OMB) data. The OMB Circular A-94 guideline recommended the use of a discount rate of 7% per year for benefit-cost analysis. The (USDOT, 2018) suggested a quantitative method of estimating the real discount rate using the interest rate and inflation as input parameters as shown in the equation below.

$$Real\ Discount\ Rate = \frac{i-f}{1-f} \qquad (28)$$

Where f is the inflation rate and i is the nominal interest rate.

The cost period is referred to as the length of study period, and is the same for all the alternatives in consideration (Fuller, 2010). Constant dollar analysis does not consider the inflation factor while the current dollar analysis accounts for inflation. Federal projects (not funded by private sector are known to use the constant dollar analysis method (Fuller, 2010). Net present value (NPV), payback period (simple and discounted payback), internal rate of return (IRR), net savings (NS), savings-to-investment ratio (SIR), and annual equivalent value (AEV) also known as the annualized value, are some of the important parameters associated with LCC (Esen et al., 2007). A summary table of various formulae has been shown in Table 4 (Grigg, 2009).

Table 4: Calculating time value of money (Grigg, 2009)

Name	**Formula**

Single payment, compound amount factor	$\frac{F}{P} = (1+i)^n$
Single payment, present worth factor	$\frac{P}{F} = \frac{1}{(1+i)^n}$
Capital recovery factor	$\frac{A}{P} = \frac{i\,(1+i)^n}{(1+i)^n-1}$
Uniform series, present worth factor	$\frac{P}{A} = \frac{(1+i)^n-1}{i\,(1+i)^n}$
Uniform series, compound amount factor	$\frac{F}{A} = \frac{(1+i)^n-1}{i}$
Sinking fund factor	$\frac{A}{F} = \frac{i}{(1+i)^n-1}$

In a Colorado Department of Transportation (CDOT) report, Demos (2006) provided a graphical representation of the inflation rate and the discount rate of the past few years as shown in Figure 10 and Figure 11.

Figure 10: Trend of inflation rate

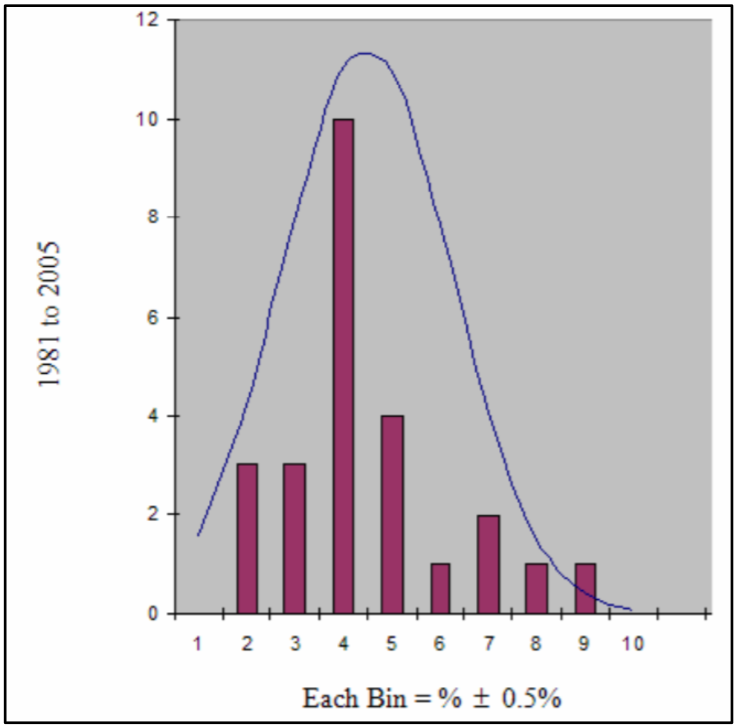

Figure 11: Histogram of discount rate

2.5.3 Life cycle costing for buildings and related quantification

LCC has been used to help with making sound environmentally friendly decisions. Pre- and post-construction impacts are often neglected and conducting an LCCA is an effective approach to account for the pre- and post-construction phases. The US Department of Defense, along with other efforts began the use of LCC for buildings evaluation in 1980s. Multiple research studies have pursued quantification of the monetary environmental impacts using the LCC (Gluch & Baumann, 2004; Mehany & Kumar, 2019). LCC for buildings have accounted for various cost variables to calculate the total as shown in Table 5.

Table 5: Cost variables in different phases of a project

Investment Cost Data	Operation and Maintenance Data	Project Specific Data
Construction Cost	Administrative Costs	Building Type
Land Acquisition Cost	Energy Costs	Building Design

Design Cost	Water Cost	Location
Salvage Value	Wastewater management Cost	Lifetime Period
Demolition Cost	Cleaning Costs	
	Maintenance and Repair Costs	
	Insurance Costs	
	Taxes	

ISO (2008) divided the building life cycle costs as design and construction cost, operation cost, maintenance cost, and end of life cost. This breakdown was adopted in multiple research studies over the years. Their representation of input data for LCC calculation for buildings by (Fuller, 2010) accounting for acquisition through the disposal phases – initial costs (purchase, acquisition, construction), fuel costs, operation and maintenance costs, repair costs, replacement costs, residual charges (resale or salvage value), finance charges (loan interest payments), and non-monetary costs and benefits. The total life cycle cost was defined as the present value of above-mentioned components and the equation has been described below.

$$LCC = I + Repl - Res + E + W + OM\&R + O \qquad (29)$$

In Equation (29), LCC is the total life cycle cost in present value (USD) of a given alternative, I is the present value of investment costs, Repl is the present value of replacement costs, Res is the present value of the residual value, E is the present value of energy costs, W is the present value of water costs, OM&R is the present value of non-fuel OM costs, and O is the present value of other costs.

Kneifel (2010) assessed various building types to identify significant life cycle cost savings by using ASHRAE 90.1-2004 compliant design. Conformed through the Energy Policy Act of 2005, this ASHRAE standard-appendix G (released around 2005) is responsible for realization of significant energy savings (thus leading to cost savings) (ASHRAE, 2004). Islam et al. (2015) summarized LCC benefits from previous studies namely, decision making tool for designers and clients, assess financial benefits of housing energy efficiency, and optimize house design. They included the present value of construction costs, maintenance, repair, replacement, energy costs, and residual value to calculate the LCC. They calculated the operation, maintenance, and demolition cost by determining the future value from the current prices as defined in Table 4. These future values were then discounted to present value using the prevailing discount rate as shown below.

$$DPV = \frac{FC}{(1+d)^n} \quad (30)$$

In Equation (30), DPV is the discounted present value, FC refers to the future cost, d is the discount rate, and n is the number of years.

Islam et al. (2015) used these concepts to graphically represent the different phases of a building over varying discounting factors as shown in Figure 12.

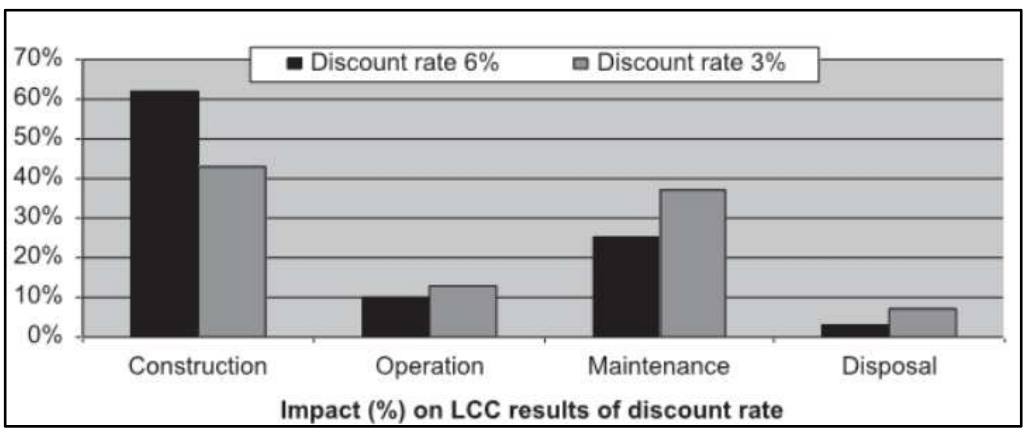

Figure 12: Dependence of discount rate on LCC

Tam et al. (2017) conducted research on determining the life cycle cost of green buildings using timber material. The capital cost of timber material, timber usage in the building, expected service life, maintenance costs, and demolition costs as some of the key datasets to calculate the LCC. All phases of the building life cycle have been clearly addressed, however, the end of life phase has had knowledge gaps, which Dwaikat and Ali (2018) were able to address. They identified two methods of reaching the end of life phase, namely demolition and deconstruction. Demolition is majorly accomplished using heavy machinery (fast) and deconstruction is a labor-intensive (slow) more sustainable approach. Recently, a hybrid demolition has been used to accelerate this process where only certain elements are deconstructed while the rest of the building is being demolished. Dwaikat and Ali (2018) also proposed using a life cycle cost baseline approach to track the cost trend for every phase of the building. Due to prolonged debate of green buildings leading to escalated costs, Li et al. (2020) used life cycle costing to determine whether the usage of more sustainable measures lower the maintenance cost and offset the higher upfront construction cost. They determined the dataset required for conducting a LCC as shown in Table 6.

Table 6: Dataset required for conducting LCC

Construction Costs	**Operation Costs**
Substructure	**Occupancy**
Superstructure	Energy
Finishes	Water
Fittings and Furnishings	Cleaning
Services	Security and Health
External Works	Management
	Maintenance and Repair
	Main Building
	Plumbing
	Electrical
	Elevators
	Communications
	Fire Protection
	Replacement

They proposed annualizing the construction costs by dividing the total construction cost by the life cycle period of any building. Thereafter, the maintenance cost per year were converted to their respective net present values. These NPVs were added to get the total operation and maintenance cost, and further divided by the life cycle period to get the corresponding annualized value. Total annualized life cycle cost was determined by adding the annualized construction cost and the annualized operation and maintenance cost (Li et al., 2020).

2.5.4 Life cycle costing for infrastructure and related quantification

Concepts developed for buildings have been used to calculate the LCC for infrastructure. Considering that the construction, operation and maintenance phases are significant longer as compared to buildings, LCC approach has been very helpful in making essential investment decisions for infrastructure project.

In an early attempt to calculate the LCC of pavements, Kulkarni (1984) defined cost subsystem – initial construction cost and material costs (including possible salvage value), routine maintenance costs, user costs including the vehicle operating costs and time delay costs, and inflation and interest rates. Several steps have been identified by Walls and Smith (1998), to conduct LCC of infrastructure projects – (1) establish alternative design strategies, (2) determine activity timing (duration), (3) establish agency costs, (4) establish use costs, and (5) determine life cycle cost. Furthermore, they quoted FHWA by proposing a minimum 35-year life cycle period and a discount rate between 3% and 5%. Salem et al. (2003) exerted the need to use probabilistic LCC due to the presence of different failure rates of various components (reason attributed to random duration of service life of components) of an infrastructure project. They used the time to failure data to fit unique probability distributions to the input parameters to calculate the total life cycle cost. Time to failure depended on the environmental conditions, deterioration rate, subgrade type, traffic volume, pavement type, and pavement thickness. Salem et al. (2003) also conducted an in-depth study of various methods for performing life cycle costing namely, present worth method, equivalent uniform annual cost method, rate-of-return method, and cost-effectiveness method, and implied that the "present worth method" presented more reliable solutions. Furthermore, they provided a method for quantification of LCC as shown in the equation below.

$$LCC_{a,n} = Ci_a + \sum_{t=0} pwf_{r,t}(Cf)_{a,t} + \sum_{t=0} pwf_{r,t}(Cmo)_{a,t} + \sum_{t=0}^{n} pwf_{r,t}(Cu)_{a,t} - pwf_{r,n}(Sv)_{a,n} \quad (31)$$

In Equation (31), $LCC_{a,n}$ is the present worth of life cycle cost for alternative a, for analysis period of n years; Ci_a is the initial capital cost of construction for alternative a; $pwf_{r,t}$ represents the present worth of future amount at time t years at prevailing discount rate; $Cf_{a,t}$ represents cost of failure (rehabilitation) for alternative a at year t; $Cmo_{a,t}$ is the cost of maintenance and operations for alternative a at year t; $Cu_{a,t}$ represents the user costs due to failure for alternative a at year t; $pwf_{r,n}$ represents the present worth of a future amount at the end of analysis period n at prevailing discount rate; $Sv_{a,n}$ is the salvage value for alternative a at the end of analysis period n; N is the number of simulations (or iterations) of Monte Carlo Simulation.

$$\sum_{t=0}^{n} pwf_{r,t}(Cf)_{a,t} = pwf_{r,t_{1-l}}(Cf_{t_1} + Cf_{t_2} + Cf_{t_3} + \cdots Cf_{t_l}) \quad (32)$$

In Equation (32), $pwf_{r,n}$ represents the present worth of a future amount at the end of analysis period n at prevailing discount rate; $Cf_{a,t}$ is the cost of failure (rehabilitation) for alternative a at year t; t_l is the sum of times to failure for "l" rehabilitations; t_{l+1} represents the sum of times to failure for "l+1" rehabilitations.

Performing the Monte Carlo Simulation of the input data provided a distribution for the life cycle costing.

Ugwu et al. (2005) provided several input datasets for calculating the life cycle cost of infrastructure projects – (1) Construction costs, (2) Cost of various risk factors, (3) recurring operation and maintenance costs, (4) and specific operation and maintenance costs. Each of these elements were further quantified by Ugwu et al. (2005) as shown below.

$$Design\ Cost_i = \sum Q_i U_i\, R_{Di} \quad (33)$$

$$Recurrent\ Cost_i = \sum A_i\, D_i R_{Ri} \quad (34)$$

$$Cost_i = \sum Design\ Cost_i + \sum Recurring\ Cost_i \qquad (35)$$

$$Total\ Cost = \sum Cost_i \qquad (36)$$

Where Design $Cost_i$ represents the structural component (i) design cost including construction cost; Recurring $Cost_i$ represents the recurring cost of component (i) in addition to the operation cost; $Cost_i$ represents the cost of given component; Q_i represents quantity of given component; U_i represents the unit cost of component; R_{Di} represents the risk factor associated with design cost estimation uncertainties; R_{Ri} represents the risk factor associated with recurrent cost estimate uncertainties; Ai represents the estimated recurring costs; and D_i represents the economic discount factor.

Singh and Tiong (2005) defined agency costs, user costs, accidents, and external costs as major components of a highway for conducting LCC. Agency costs include the initial cost, rehabilitation cost, prevention and maintenance costs, and disposal costs of a road or highway. They identified the vagueness of road user cost in previous studies and demonstrated the quantification as shown below.

$$Road\ user\ cost = CDT + CAF + CAM \qquad (37)$$

Where CDT is the delay time; CAF represents the cost of additional fuel consumption; and CAM is the cost of additional maintenance of a vehicle. The LCC is calculated using present values of the variables as shown in Equation (37).

$$PW\ of\ LCC = Initial\ cost + PW\ (Maintenance\ cost + User\ cost) \quad (38)$$

Infrastructure LCC's accuracy heavily depends on the accuracy of input parameters and therefore, Scheving (2011) suggested using sensitivity analysis for the input parameters. They also construed the data from multiple pavement projects across the globe to find that the cost affects multiple stakeholders namely, general public, road users, general contractor, manufacturers, suppliers, road and street agencies, senior administrators, elected officials of the government, and consultants. Therefore, using life cycle cost to make decisions regarding the project can be a challenging and impactful.

A tradeoff between the use of concrete pavement and precast-concrete pavements have been studied to determine most efficient paving technique and reduce the overall project duration and the life cycle cost. Moreover, prestressed precast-concrete pavement has been found to have lower maintenance needs resulting in lower maintenance costs (Sompura & Avetisyan, 2017). They considered the initial construction cost (only activities related to pavement construction), present value of maintenance and rehabilitation (cost of materials, equipment, staff etc.), present value of user costs (vehicle operating costs, user delay costs, and crash costs), present value of operating costs, and present value of salvage value (residual as recycled material) to calculate the total life cycle cost (Sompura & Avetisyan, 2017).

The above research studies show that an informed investment ensues when life cycle cost assessment is used on the projects (Singh & Tiong, 2005). Even though investment nodes' selection can be made through LCC, it is essential to consider the level of sustainability, level of resilience, and the project duration for each of those nodes. Therefore, various tradeoffs have been explained in the next section which have been historically solved using optimization.

2.6 Tradeoffs and Optimization

2.6.1 Tradeoffs

Boarnet (1997) implied that sustainability planning does not always require a tradeoff between economic, social, and environmental objectives, but rather finding strategies that help achieve all these objectives over the long term by increasing transportation system efficiency. These strategies compete in cost aspects and careful selection is made using optimization (discussed in the next few sections) (Tupper et al., 2012). Replogie (1991) suggested a long-term cost assessment of various sustainable strategies to optimize the impacts with respect to the total life cycle costs. This idea was further echoed in a research conducted by Schraven and Hartmann (2010), who found a tradeoff between public interests (e.g. affordability, sustainability, safety, accessibility, and robustness) and financial investments and suggested efficient decision making by involving the community and including the life cycle assessment of various options. Reuter et al. (2012) emphasized that careful assessment of selecting the material (and its supplier) as there is a tradeoff between sustainability and cost; using unsustainable practices at any phase of supply chain can negatively impact the economic bottom line. Implementation of resilient strategies need to be sustainable to reduce the environmental, social, and economic impacts, therefore suggesting that there is a tradeoff between resilience and sustainability (Salas & Yepes, 2020).

2.6.2 Optimization

Optimization is a mathematical method to maximize or minimize certain values/set of variables within a set of constraints to determine the best solution, among a pool of choices (UWASH, 2015). In mathematical optimization, a mathematical function is formulated and minimized or maximized depending on the required logic. The result obtained after a certain number of iterations would be the best possible minimum or maximum value, also known as the Optimum value for the variable (Boyd & Vandenberghe, 2004). Deb (2014) (page V), defined the Optimization as "the task of finding one or more solutions which correspond to minimizing or maximizing one or more specified objectives, and which satisfy all constraints (if any)."

Optimization can also be used for multiple objectives that need to be maximized or minimized at the same time which requires a different approach than a single objective optimization problem. The multiple objectives can be optimized using "Multi-Objective Optimization" which takes into consideration several contrary objectives. The multi-objective optimization solution is not a single optimal value, instead, a set of optimal values are obtained among which there is a tradeoff (Deb, 2014). Optimization, however, is not a new technique, but has existed since ancient times as discussed in the following section.

2.6.2.1 History of Optimization

The earliest work of optimization can be traced back to Greek Mathematicians when Euclid considered the minimum distance between a point and a line in 300 BCE (Cha, 2007). In 100 BCE, Heron proved that light travels between two points through the path with shortest length when reflecting from a mirror (Jenkins & White, 1957). Isaac Newton and Leibnitz created the calculus of variation which opened doors to finite optimization problems (Bertsekas, 1982). In 1784, G. Monge investigated one of the first combinatorial optimization problems known as the transportation problem (Schrijver, 2005). The 19th century saw the advent of first algorithms presented by Weierstrass, Steiner, Hamilton and Jacobi which further developed the calculus of variation (Grosholz & Breger, 2013). In 1826, Fourier formulated the Linear- Programming method to solve problems in mechanics and probability theory. By the 1870s, the works of Walras and Cournot made optimization an integral part of the economic theory (Novshek & Sonnenschein, 1978). In the 20th century, the calculus of variation was further developed by Bolza, Caratheodory, and Bliss while Hancock published the first book on optimization, "Theory of Minima and Maxima" in 1917. After World War II, optimization techniques rapidly developed with operational research. In 1944, Von Neuman used the idea of dynamic programming which works on the principle of breaking down a big problem into smaller subsets of problems and solving them. The solution subsets would be stored in the memory and could be used in the future if encountered by a similar problem subset (Backus, 1978). In 1951, Kuhn and Tucker invented optimal conditions for nonlinear problems (Kuhn, 2014) and by the 1980s, the heuristic algorithms for global optimization and large-scale problems were developed as computers became more efficient in computation capabilities (Mandl, 1980). After 1990s, complex algorithms were developed and used in the optimization process thereafter (Kiranyaz, Ince, & Gabbouj, 2014). The first widespread application of optimization was in the manufacturing industry.

2.6.2.2 Optimization in Manufacturing

One of the early major problems encountered by the manufacturing industry was to "schedule scarce resources among different manufacturing demands" (Cai & Li, 2012). This required an optimization of the resources' distribution among the different projects to ensure efficient utilization of the capital invested in these resources during the manufacturing process (Cai & Li, 2012). After 1980s, automation was required in supply chain management due to the increased product demands when Ascheuer (1995) used optimization to minimize the loading and unloading times of automated storage systems. In the 21st century, the technology became more advanced, and the market grew further due to the higher demands, all which required different methods to solve a larger scale problem.

Chen and Lee (2004) incorporated another variable factor i.e., price and used multi- objective optimization of supply chain networks with uncertain product demands and prices. Altiparmak et al. (2006) solved a non- linear programming model for multi- objective optimization of Supply chain network design by using genetic algorithm to minimize cost and maximize customer service and capacity utilization, as the three main objectives. Pishvaee, Rabbani, and Torabi (2011) devised a robust optimization approach to a "closed- loop" supply chain network design under the uncertainty of fluctuation demands in different markets.

Lagging behind the manufacturing industry, the optimization technique had been utilized in the construction industry to solve major tradeoffs and optimize resource utilization.

2.6.2.3 Optimization in Construction

Optimization was introduced in the construction industry to solve different tradeoffs that overburdened the decision-making process. Quality is one of the most difficult factors to quantify; El-Mikawi (2005) prioritized factors based on information from construction site (provided by project manager/superintendent), to calculate the quality of a project. Time and cost constraints in any construction project are closely associated with the utilization of resources. Resource utilization is a critical constraint for optimizing the time and cost in construction projects and avoid delays and cost overruns (Christodoulou, Ellinas, & Aslani, 2009). Lucko (2011a) emphasized the need for smart resource modelling into linear scheduling to enhance resource utilization efficiency in repetitive operations. Several scholars have used Genetic Algorithm as the computational technique to solve resource constrained problems and others used it with local search and hyper heuristic techniques (Anagnostopoulos & Koulinas, 2010) to solve resource constrained problems.

In solving these aforementioned tradeoffs, Genetic Algorithm (GAs), Particle Swarm Optimization, Simulated Annealing, Ant Colony Optimization, and Artificial Neural Networks (ANNs) were some of the different programming algorithms used to solve the different optimization problems in construction. These programming algorithms require a large amount of data input, pertaining to the variability of the tradeoffs, and going through a number of iterations to reach the final result represented in a set of optimal values. Several research efforts were pursued for optimization in infrastructure.

2.6.2.4 Optimization in Infrastructure

2.6.2.4.1 Optimization of Resilience and Sustainability in Infrastructure

Chen and Miller-Hooks (2012) proposed a bilevel optimization model to compute reliability and flexibility of freight transportation to imply that the recovery activities were essential in optimizing the resilience. Bocchini (2013) used genetic algorithm to optimize the disaster management of transportation networks and achieve minimization of short-term emergency response and maximization of system restoration.

Chelleri et al. (2015) suggested that a resilience framework should always be associated with sustainability by implementing their conceptual framework on three case studies. Therefore, the tradeoff between resilience and sustainability is a growing concern that needs to be optimized. Krishnan et al. (2015) developed a passenger transportation network model to investigate long-term transportation planning. They formulated an optimization framework to solve the tradeoff between operations and investments while accounting for interdependencies between the transportation and energy sectors. Krishnan et al. (2015) further emphasized the purpose of using a large-scale multi-sector model as being able to achieve cost minimization, more sustainable and resilient infrastructure, while accounting for interdependencies.

Faturechi and Miller-Hooks (2015) performed a comprehensive literature review and developed a qualitative decision support system to optimize the pre- and pos-disaster investments to maximize the coping capacity of the system and minimize the losses. Multiobjective evolutionary algorithm (non-dominated sorting genetic algorithm) was developed to optimize the design configurations of systems subjected to earthquakes and floods related hazard events while maximizing resilience and minimizing retrofit costs (Chandrasekaran & Banerjee, 2016).

Ibanez et al. (2016) identified electricity production and transportation networks as two intertwined infrastructure systems and proposed optimal designs of future power generation, its transport and storage, and hybrid-transportation systems in a sustainability, cost, and resilience tradeoff solved using a NETPLAN tool. Using this NETPLAN optimization model, Ibanez et al. (2016) found pareto surface of optimal solutions. A pareto surface was defined as "the collection of solutions that are non-dominated" while a non-dominated solution was defined as another better solution to the objectives being non-existent. NETPLAN used a non-dominated sorting genetic algorithm (NSGA-II) as it preserved the breadth of solution space; the cost investment options were used to compute the sustainability (calculated in terms of environmental impact and supply longevity) and resilience metrics (computed as an operational increase of cost over time due to each event). A novel approach for calculation of resilience was suggested by Ibanez et al. (2016) while solving tradeoffs by identifying the hazards that are most frequent and cause the most loss to the infrastructure system. Resilience to one hazard type does not guarantee the resilience to other hazard types.

Homayounfar et al. (2018) identified a tradeoff between resilience and robustness unlike the widely accepted opinion of robustness being a part of resilience. The resilience and robustness variables were subject to public infrastructure provider constraint (investing too much in the maintenance project leading to investment shortage and abandonment of projects) and stability condition of non-trivial point (defines a minimum level of service for the citizens) which helped shape future policies. The results present a set of pareto-optimal policies that solve the tradeoff between robustness and resilience (Homayounfar et al., 2018). Bocchini et al. (2014) imposed that sustainability and resilience were complementary and recognized the existence of tradeoff between the two theories. Furthermore, Bocchini et al. (2014) combined resilience and sustainability while accounting for the hazardous events as in Equation (39).

$$I = \sum_{e \in E_r} P_e . I_e + \sum_{e \in E_s} P_e . I_e \quad (39)$$

Where I is the expected life cycle of infrastructure, E_r and E_s are resilience and sustainability domains, P_e is the probability of event occurrence, and I_e is the impact on community. Lastly, these authors encouraged future research to incorporate probabilistic scenarios when optimizing resilience and sustainability.

Salas and Yepes (2020) developed an optimization model to enhance the sustainability and resilience through multi-level infrastructure planning. They identified a lack of research in implementing resilience strategies that are also sustainable. A multi-objective model helped in identification of key planning alternatives and their impact on vulnerable entities and the results showed a strong correlation between planning alternatives and risks associated. Recently, a new framework was developed to address the tradeoff between resilience, sustainability, and security (level of service) and applied it to seven different cities. An optimization model was used to determine the pareto front that indicated the maximization of sustainability while minimizing the associated risk and reducing the global footprint of each of the cities (Krueger et al., 2020). Valenzuela-Venegas et al. (2020) introduced an optimization model to solve five objectives – individual considerations of economic sustainability, environmental sustainability (failed to account for social sustainability), resilience; tradeoff between economic and environmental sustainability; and simultaneous consideration of economic sustainability, environmental sustainability, and resilience. They glorified the importance of solving single objectives as it provided the best alternative for each objective. Multiple objectives on the other hand establishes the best alternative that maximizes the resilience and sustainability.

2.7 Research gaps and problem statement

The literature review explored sustainability and resilience in detail and identified the wide disparity in definition and quantification of these terms. Sustainability was found to have a more consistent approach to defining terminologies and quantifying the various dimensions compared to resilience. Additionally, there have been several opposing arguments that addressing sustainability hinders resilience adoption and addressing resilience hinders sustainability. Currently, there is no literature synthesis on sustainability and resilience that covers the various definitions and the different quantification techniques used. Due to this gap, it is difficult for both the research community and the transportation stakeholders to agree on the adoption of sustainability and resilience in transportation projects. Therefore, this research explores the integration of sustainability and resilience. Under most circumstances, the discussion of sustainability just resolves around reducing the greenhouse gas emissions (GHGs emissions). However, this research is attempting to promote the adoption of social, environmental, and economic sustainability while building a transportation infrastructure. Numerous quantification techniques exist that can be used to assess the dimensions (TBL) of sustainability but using infrastructure rating system provides a standardized metric. Similarly for resilience, no research has created a model that can improve the decision making when resilient initiatives are being incorporated into the construction of a transportation infrastructure. ENVISION has been selected as the rating system to quantify sustainability and resilience of the transportation infrastructure in the US. Transportation service consumers and the stakeholders have had difficulty in selecting strategies that would have a lower life cycle cost (LCC), and they are often focused on the initial cost of the infrastructure. This research presents a model wherein strategies can be selected to ensure the total initial cost falls within the allocated budget and prioritizing the options with lower LCC.

Sustainability and resilience measures affect a variety of different factors such as the initial cost (also known as the first cost), life cycle cost (LCC), greenhouse gas emissions (GHG emissions), project duration, operation and maintenance duration, and disaster recovery duration. Among all these factors, the factors which had the most impact and for which most data were available, were chosen for the optimization purposes. In this research, a tradeoff has been observed between sustainability, resilience, LCC, and GHG emissions. Even though there are credits to address LCC and GHG emissions in the ENVISION rating system, these two have been separated as unique objectives to promote the selection of strategies that fall within certain parameters. For example, increasing sustainability does not necessarily mean that the credit responsible for conducting LCC and reducing GHG emissions will be addressed. A common perception associated with sustainability and resilience is that the strategies used to adopt them are expensive and not worth the effort. This research attempts to provide evidence of implementation of sustainability and resilience within budget.

This research aims to ***achieve a higher level of sustainability and resilience for transportation projects within constrained budgets and through their entire life cycle***. To address this problem, a few research questions were detailed which helped to elaborate the objectives for this research.

2.8 Research questions and objectives

Several research questions were identified after identifying the problem statement to address the research gap identified above:

1. How is sustainability and resilience defined and quantified?
2. How does the adoption of sustainability compete with resilience and vice versa? How does the adoption of sustainability support resilience adoption and vice versa?
3. How are the LCC, and GHG emissions effected by the adoption of sustainability and resilience?
4. How can a project achieve a higher level of sustainability while minimizing the LCC, and the GHG emissions within budget?
5. How can a project achieve a higher level of resilience while minimizing the LCC, and the GHG emissions within budget?
6. How can a project resolve the tradeoffs between a higher level of sustainability and resilience while minimizing the LCC, and the GHG emissions under budget constraints?

These research questions were answered using the following objectives:

1. **Objective 1**: To explore, compare, and contrast the definitions and quantification of sustainability and resilience.
2. **Objective 2**: Create a novel model that can maximize sustainability while minimizing LCC, and GHG emissions

3. **Objective 3**: Create a novel model that can maximize resilience while minimizing LCC, and GHG emissions
4. **Objective 4**: Create a novel model that can maximize sustainability and resilience while minimizing LCC, and GHG emissions

A graphical representation of the connection of the research questions with the objectives has been shown in Figure 13.

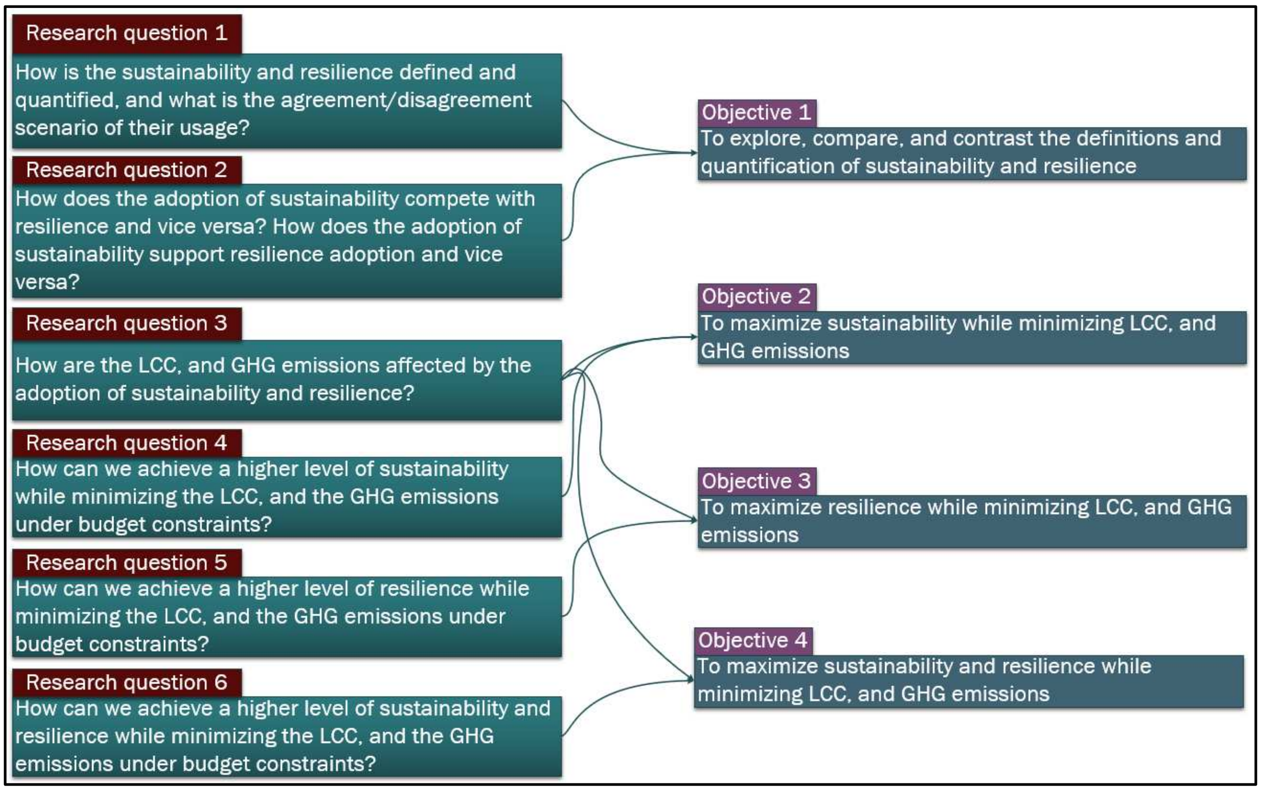

Figure 13: Connecting research questions and objectives

The research objectives help in answering the research questions defined above. These objectives have been addressed through the various research phases in the methodology section.

3 Methodology

3.1 Overview

Transportation projects are the main focus of this dissertation and all phases defined above are sequential. Among all the rating systems discussed in the 2.2.5 Sustainability Measurement and Rating Systems section, ENVISION has been selected as the quantification standard for this research. Due to ENVISION being the basis of the new ASCE sustainability standard and being widely used in the US, it is best suited for creating models in this research (ASCE, 2021a). ENVISION rating system has been described in detail in the section **2 Literature review**. The five categories under ENVISION can be broken down into two of the pillars of sustainability namely social sustainability and environmental sustainability. Quality of life and leadership categories contain credits which drive the social sustainability; resource allocation, natural world, and climate categories contain credits which drive the environmental sustainability. Quality of life category relates to the health and wellbeing of a community and how it is affected by the project. It promotes the involvement of community members in the decision-making process and therefore this category addresses the social aspect of sustainability. The leadership category deals with finding an effective way to deliver projects while reduce the resource consumption and assisting in life cycle benefits from the project, thereby reaping social benefits. Therefore, this category pertains to social sustainability. Resource allocation relates to judicious use of water, energy, and materials in both the construction and the operations phase to improve the environmental sustainability. Natural world captures the protection of natural habitats and all nonliving systems and emphasizes that any project does not have negative impacts or provides features which enable a positive interaction between the natural system and the project. This category relates to the environmental sustainability as well. Though the climate and resilience section of ENVISION captures both sustainability and resilience, only the sustainability aspect has been accounted for in this phase. Climate section relates to reducing the impact of all contributors to the climate change through the life cycle of the project. Therefore, it relates well to the environmental sustainability. The institute of sustainable infrastructure (ISI) proposes using ENVISION framework for measuring the sustainability of infrastructure projects. Finkbeiner et al. (2010); Klöpffer (2008) validates the idea of considering LCC to represent economic sustainability.

The research follows a four-phased methodology to address all the objectives and associated research questions defined in the sections above:

1. Phase 1: Synthesis of sustainability and resilience concepts based on comprehensive literature review
2. Phase 2: Sustainability (triple bottom line) optimization model
3. Phase 3: Resilience optimization model
4. Phase 4: Integrated sustainability-resilience optimization model

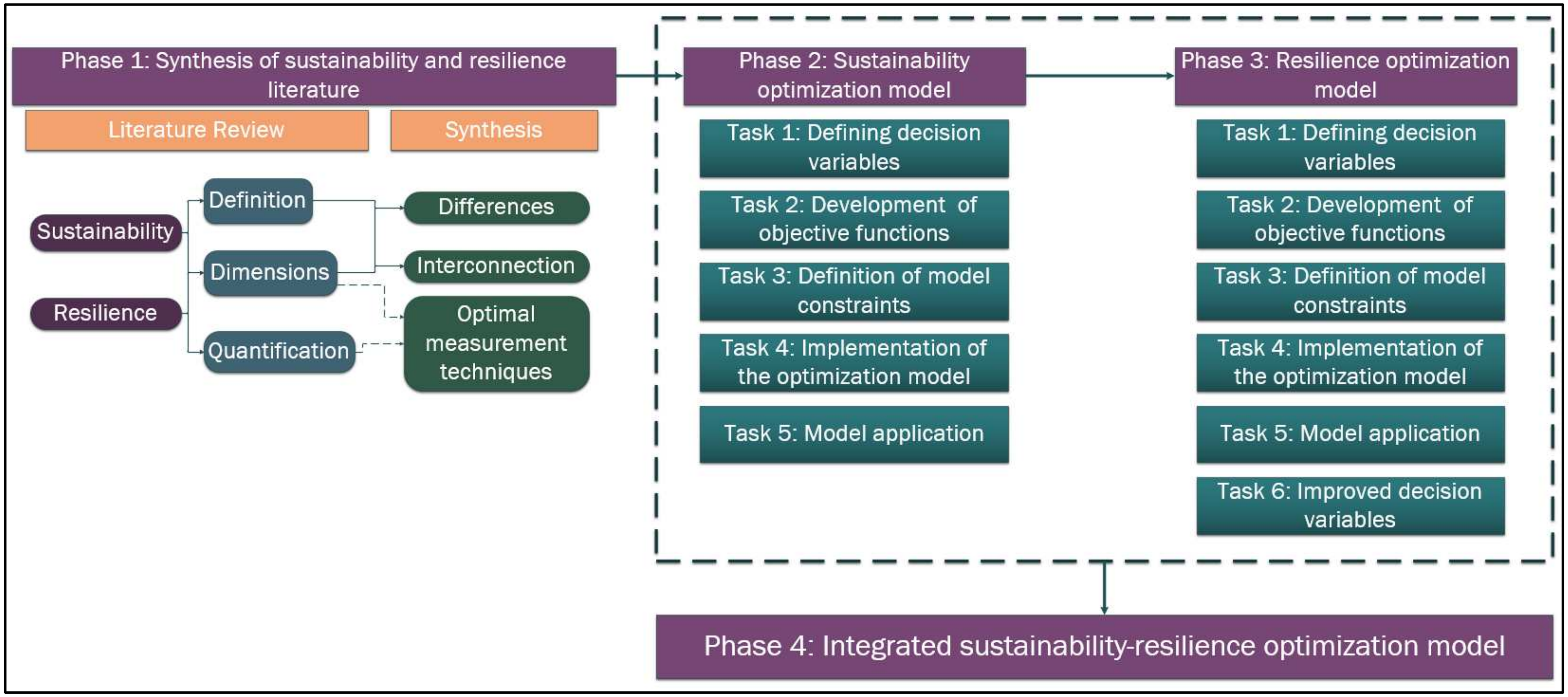

Figure 14: Research design

These phases have been graphically represented in Figure 14. **Phase 1** involves synthesizing the literature and understanding the various perceptions associated with sustainability and resilience. **Phase 2** is focused on the optimization of sustainability in transportation projects wherein the tradeoff exists between duration metrics, LCC, and level of sustainability. This level of sustainability is defined by ENVISION credits. This phase entails optimization model formulation (defining the decision variables, objective function, and constraints), model implementation using unique algorithm(s), and application of the model to a case study. **Phase 3** involves optimization of resilience for transportation projects wherein the tradeoff exists between duration metrics, LCC, and level of resilience. This level of resilience is defined by the mini-rating system developed to measure infrastructure resilience. This phase entails optimization model formulation (defining the decision variables, objective function, and constraints), model implementation using unique algorithm(s), and application of the model to a case study. **Phase 4** involves optimization of an integrated sustainability and resilience framework wherein the tradeoffs exist between duration metrics, LCC, sustainability, and resilience. To cohesively think about sustainability and resilience, interconnectivity between the credits used to measure sustainability (ENVISION credits) and resilience (mini-rating system) are developed. This phase entails optimization model formulation (defining the decision variables, objective function, and constraints), model implementation using unique algorithm(s), and application of the model to a case study.

3.2 Phase 1: Integration of sustainability and resilience based on the comprehensive literature review

This phase has been divided into two parts; the first part is focused on conducting a comprehensive literature review, and the second part contains synthesizing the literature. The literature review was conducted systematically starting with a search for articles focusing on the state of the US infrastructure (especially the transportation infrastructure). Thereafter, sustainability and resilience definitions were explored and the various dimensions of each were analyzed. The quantification of sustainability and resilience was detailed, which mainly consisted of various assessment metrics (quantitative, qualitative, or mixed) or the application of various rating systems (ENVISION, CEEQUAL, AGIC/IS). In the second part, the gathered literature was analyzed and synthesized through a three-layered investigation. The differences between the definition of sustainability and resilience were observed. Thereafter, the differences between the dimensions of sustainability and resilience were understood. The interconnection between the broader concepts of sustainability and resilience and their dimensions was further examined. Hereafter, the measurement techniques for sustainability and resilience, and their associated dimensions was detailed to find the optimal measurement technique(s) for infrastructure projects.

3.3 Phase 2: Sustainability (triple bottom line) optimization model

This phase aims at creating of a sustainability optimization model to solve the tradeoff between sustainability, life cycle cost (LCC), and greenhouse gas emissions (GHGs). Sustainability in this model is defined as the triple bottom line (TBL) of social, environmental, and economic sustainability. Social and environmental sustainability are measured using ENVISION credits in this phase, and the economic sustainability has been represented by the LCC. Phase 2 is divided into 5 as shown in Figure 15 where every 5 tasks have been further divided into subtasks.

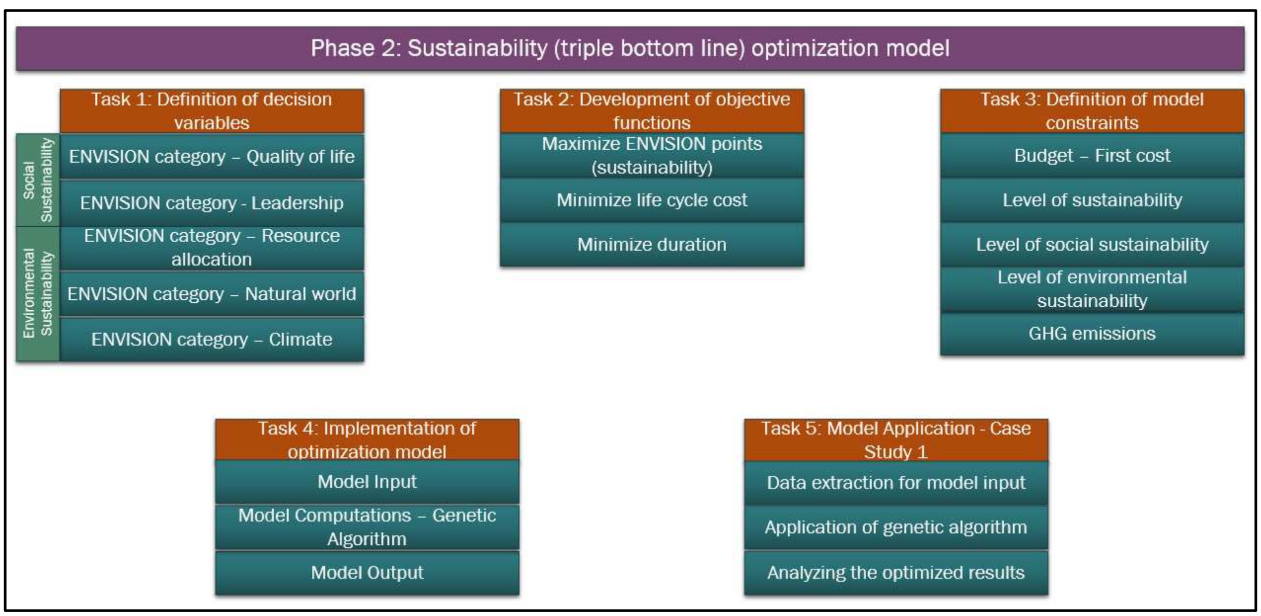

Figure 15: Sustainability optimization model mapping

3.3.1 Task 1: Definition of decision variables

A decision variable is "an unknown of mathematical optimization models" which a user would like to determine (Jensen, 2004). This task uses the decisions variables to represent feasible alternatives which was successfully implemented by Abdallah (2014), to represent different decision variables. These decision variables fall in multiple categories: (1) quality of life, and (2) leadership, (3) resource allocation, (4) natural world, (5) climate, (6) energy consumption, (7) water consumption, (8) materials, and (9) waste management. Credits under each of the categories assist in obtaining different number of points that define the level of achievement for each credit, thereby defining the level of sustainability for any transportation project. Figure 16 provides a visual representation of decision variables based on the ENVISION rating system.

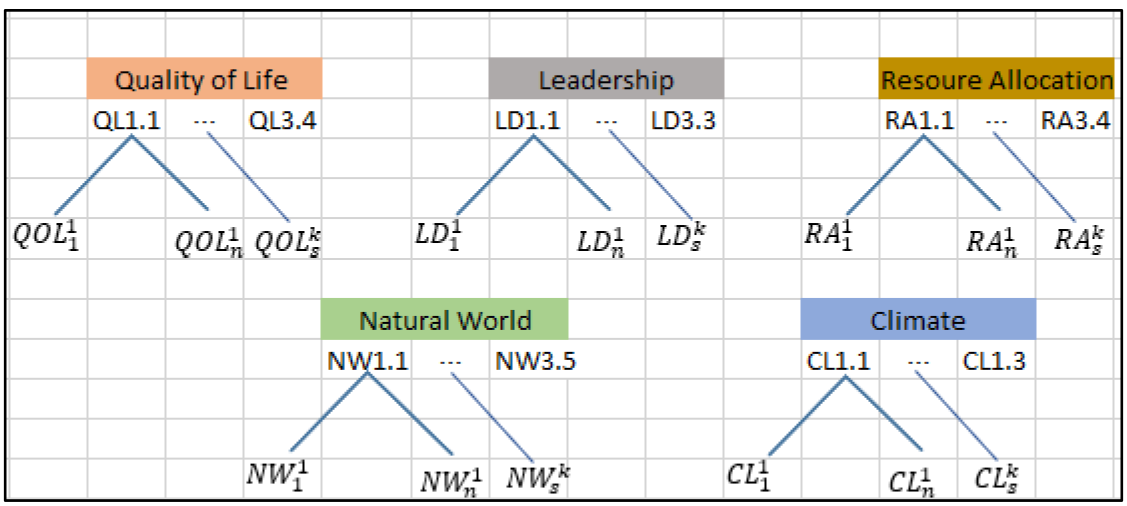

Figure 16: Decision variables derived from ENVISION

Figure 16 provides a graphical representation of five different decision variables as they relate to different ENVISION categories. Decision variables for the quality-of-life category have been defined as QOL_s^k wherein 'k' signifies each of the credits under the quality of life category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from

1 to 13 and ‘s’ ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, QOL_2^3 means that for QL1.3 credit (Improve construction safety), strategy II has been selected which helps in improving the safety of public and workers on construction site for a transportation project.

Decision variables for the leadership category have been defined as LD_s^k wherein ‘k’ signifies each of the credits under the leadership category and ‘s’ signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. ‘k’ ranges from 1 to 11 and ‘s’ ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, LD_3^1 means that for LD1.1 credit (Provide effective leadership and commitment), strategy III has been selected which promotes effective leadership and commitment in the project team to achieve the sustainability goals of a transportation project.

Decision variables for the resource allocation category have been defined as RA_s^k wherein ‘k’ signifies each of the credits under the resource allocation category and ‘s’ signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. ‘k’ ranges from 1 to 13 and ‘s’ ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, RA_1^7 means that for RA2.2 credit (Reduce construction energy consumption), strategy I has been selected which reduces the total energy consumption to further result in reduction of greenhouse gas (GHGs) emissions and air pollutants during construction of a transportation project.

Decision variables for the natural world category have been defined as NW_s^k wherein ‘k’ signifies each of the credits under the natural world category and ‘s’ signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. ‘k’ ranges from 1 to 13 and ‘s’ ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, NW_2^{11} means that for NW3.3 credit (Maintain floodplain functions), strategy II has been selected which helps maintain the floodplain functions by minimizing the development in or near a floodplain while executing a transportation project.

Decision variables for the climate category have been defined as CL_s^k wherein 'k' signifies each of the credits under the climate category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 3 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, CL_1^1 means that for CR1.1 credit (Reduce net embodied carbon), strategy I has been selected which reduces the net embodied carbon over the life cycle of a transportation project by accounting for raw material and its transportation to project site.

Furthermore, other decision variables which help achieve points in the ENVISION rating system have been shown in Figure 17.

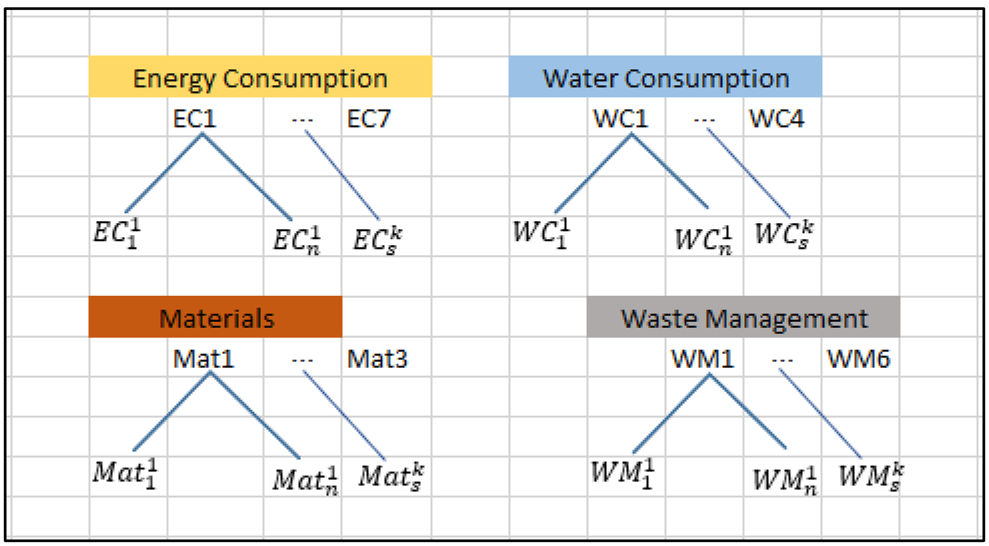

Figure 17: Other decision variables driving sustainability

The energy consumption decision variable has been defined as EC_s^k wherein 'k' signifies the various sources of energy consumption in this model namely, trucks for transportation, compaction equipment, soil stabilization equipment, dozers and graders, scrapers, excavators, and street lighting (Peurifoy et al., 2018). 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 7 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, EC_1^1 means that for EC1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The water consumption decision variable has been defined as WC_s^k wherein 'k' signifies the various sources of water consumption in this model (predominantly in road median landscaping) namely, sprinkler system, water sprinkled by water trucks etc. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 2 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WC_1^1 means that for WC1 (sprinkler system), strategy I has been selected which signifies one of the alternatives of sprinkler system type.

The materials decision variable has been defined as Mat_s^k wherein 'k' signifies the major materials which have the highest share of the total cost namely, asphalt, concrete, and excavation and backfill. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 3 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, Mat_1^1 means that for Mat1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The waste management decision variable has been defined as WM_s^k wherein 'k' signifies the various sources of waste management in this model namely, waste reduction, reuse/recycle on site, materials sent to recycling facilities, materials sent to manufacturer, composting, and materials sent to landfills. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 6 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WM_1^1 means that for WM1 (waste reduction), strategy I has been selected which signifies one of the alternatives for waste reduction.

3.3.2 Task 2: Development of objective functions

The objective functions are developed to address the tradeoffs defined above for the **phase 2**. These siloed objective functions help achieve – (1) maximization of points associated with each of the ENVISION credits under social sustainability, (2) maximization of points associated with each of the ENVISION credits under environmental sustainability, (3) minimization of life cycle cost (LCC), and (4) minimization of the GHG emissions.

Social sustainability objective function

The social sustainability objective function attempts to maximize the number of points associated with social sustainability (quality of life and leadership categories) in the ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ SS(S) = \sum_{k=1}^{13} Pts(QOL_s^k) + \sum_{k=1}^{11} Pts(LD_s^k) + \sum_{k=1}^{7} Pts(EC_s^k) + \sum_{k=1}^{2} Pts(WC_s^k) + \sum_{k=1}^{3} Pts(Mat_s^k) + \sum_{k=1}^{6} Pts(WM_s^k) \quad (40)$$

In Equation (40), social sustainability is calculated as a function of strategies under the quality of life and leadership category of ENVISION which have unique number of points for each of the credits under those categories. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's social sustainability points. These points are added together to find the level of social sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 18.

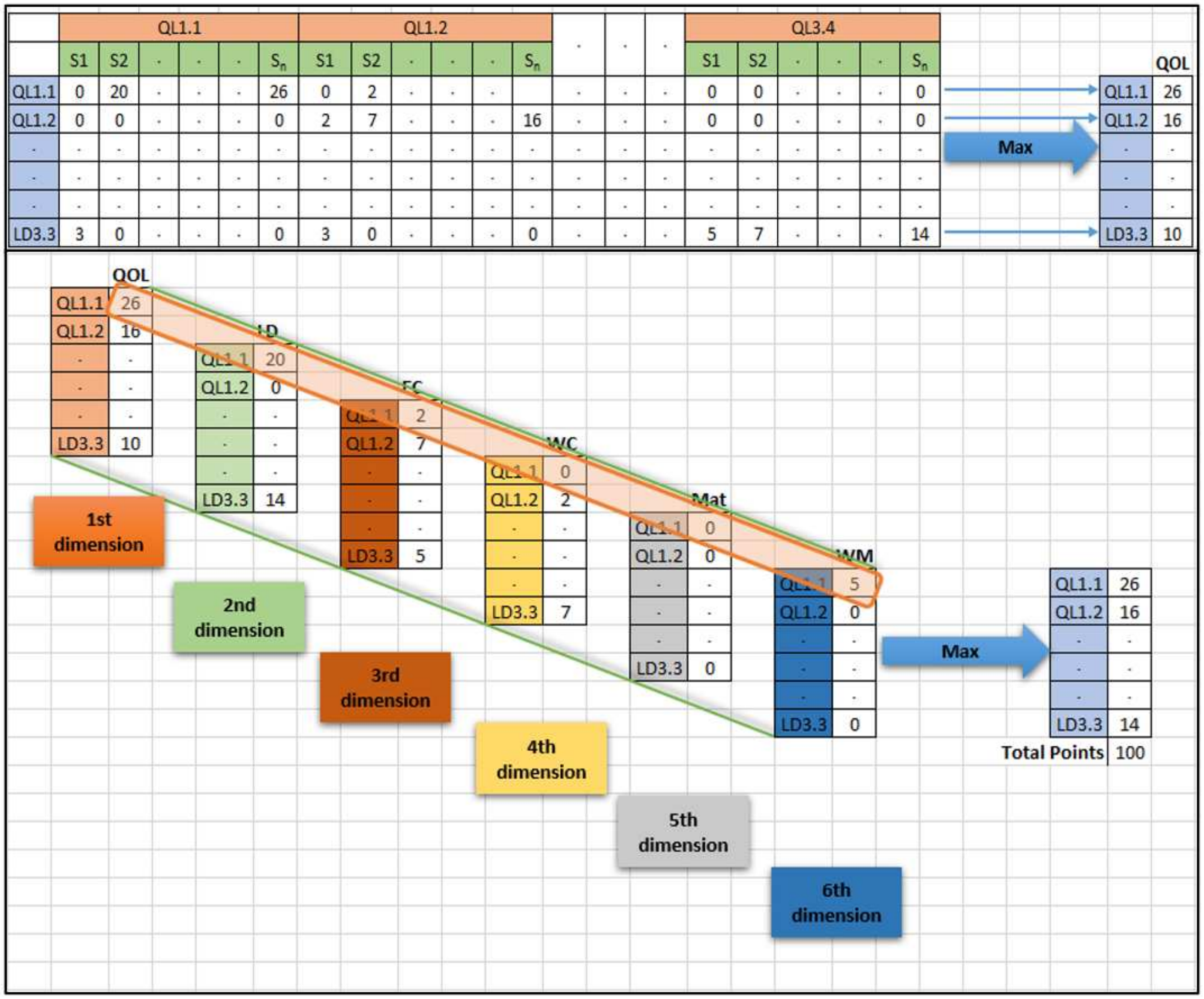

Figure 18: Points calculation methodology – Social Sustainability

As can be seen from Figure 18, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (40)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the nine main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (40). Take credit QL 1.1 (improve community quality of life) for example. This credit can be achieved by the strategies within this credit. Additionally, other credits that have a connection to QL 1.1 (for instance, QL 1.2) will be able to gain points for QL 1.1. For the quality-of-life category, all these points gained for QL 1.1 credit are tabulated in a 2D matrix and the maximum value for QL 1.1 number of points is considered. The sample output looks like the QOL matrix in the above figure. Similar matrices are created for other categories in ENVISION. Each of these categories serves as a 2D matrix in a separate dimension. Quality of life is in the first dimension, leadership category in the second dimension, and so on. The maximum value for each credit is calculated in this multi-layered matrix to ensure that none of the credits' points are counted twice. After calculating maximum points associated with each credit, the total points can be calculated by a simple addition of points within each credit. In total, we have six dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with social sustainability need to be maximized.

Environmental sustainability objective function

The environmental sustainability objective function attempts to maximize the number of points associated with environmental sustainability (resource allocation, natural world, and climate categories) in the ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ EnvS(S) = \sum_{k=1}^{13} Pts\left(RA_s^k\right) + \sum_{k=1}^{11} Pts\left(NW_s^k\right) + \sum_{k=1}^{3} Pts\left(CL_s^k\right) + \sum_{k=1}^{7} Pts\left(EC_s^k\right) + \sum_{k=1}^{2} Pts\left(WC_s^k\right) + \sum_{k=1}^{3} Pts\left(Mat_s^k\right) + \sum_{k=1}^{6} Pts\left(WM_s^k\right) \qquad (41)$$

In Equation (41), environmental sustainability is calculated as a function of strategies under the resource allocation, natural world, and the climate categories of ENVISION which have unique number of points for each of the credits under those categories. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's environmental sustainability points. These points are added together to find the level of environmental sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 19.

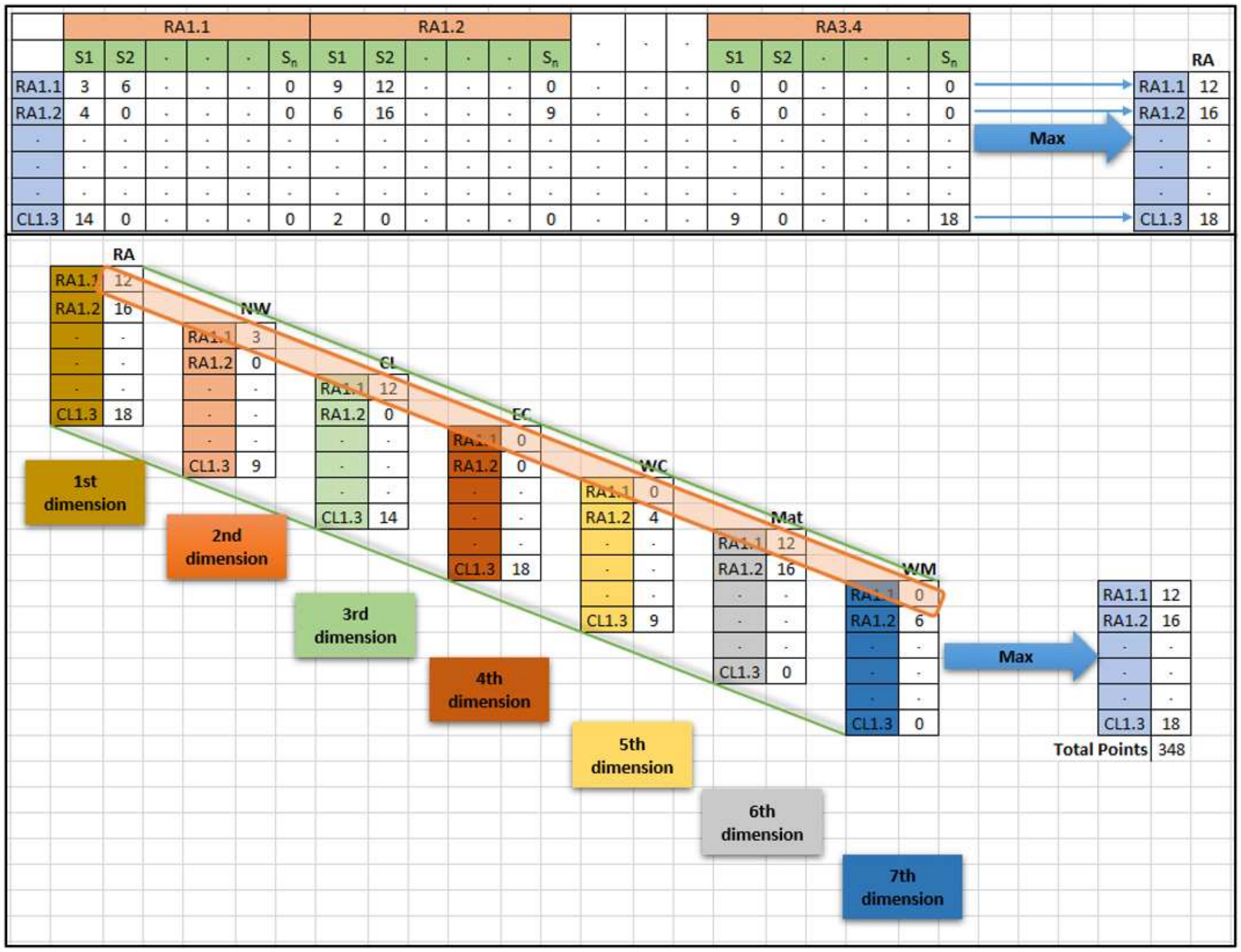

Figure 19: Points calculation methodology – Environmental Sustainability

As can be seen from Figure 19, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (41)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the nine main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (41). Thus, in this case, we have seven dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with environmental sustainability need to be maximized.

Life cycle cost objective function

The life cycle cost (LCC) objective function attempts to minimize the life cycle cost associated with the strategies adopted within the nine decision variables (Scheving, 2011; Sompura & Avetisyan, 2017).

$$Min\ LCC(S) = \chi_o + \left\{\sum_{n=1}^{LC/15} \frac{Y}{(1+i)^{15n}} + \sum_{n=1}^{LC/5} \frac{Z}{(1+i)^{5n}}\right\} - \frac{S}{(1+i)^N} \quad (42)$$

$$S = P - (Annual\ Depreciation \times Useful\ life) \quad (43)$$

Here χ_o refers to the initial cost (or first cost) of the strategies as described in Equation (44). The computation of Y and Z corresponds to the operations and maintenance phase. It consists of rehabilitation cost (variable Y) signifying the maintenance, and street lighting and water consumption costs (variable Z) signifying the operations. It has been determined that the rehabilitation of a road projects should be done every 15 years on an average and the maintenance activities are usually done every five years (Portland Bureau of Transportation, 2021). Therefore, the values for variable Y have been calculated and added together, after every 15 years throughout the life cycle; values for variable Z have been calculated and added together after every five years throughout the life cycle. Variable S determines the salvage value as defined in Equation (42).

$$\chi_o = \sum_{k=1}^{13} IC(QOL_s^k) + \sum_{k=1}^{11} IC(LD)_s^k + \sum_{k=1}^{13} IC(RA_s^k) + \sum_{k=1}^{13} IC(NW_s^k) + \sum_{k=1}^{3} IC(CL_s^k) + \sum_{k=1}^{7} IC(EC_s^k) + \sum_{k=1}^{2} IC(WC_s^k) + \sum_{k=1}^{3} IC(Mat_s^k) + \sum_{k=1}^{6} IC(WM_s^k) \quad (44)$$

Here IC represents the initial cost; IC(QOL) means initial cost as a function of quality-of-life strategies.

$$Y = \sum_{k=1}^{7} RC(EC_s^k) + \sum_{k=1}^{2} RC(WC_s^k) + \sum_{k=1}^{3} RC(Mat_s^k) \quad (45)$$

RC represents the rehabilitation cost; RC(EC) means rehabilitation cost as a function of energy consumption strategies.

$$Z = \sum_{k=1}^{7} OC(EC_s^k) + \sum_{k=1}^{2} OC(WC_s^k) \quad (46)$$

OC signifies the operations cost; OC(EC) signifies the operating cost of street lighting throughout the life cycle of the project. OC(WC) means operating cost as a function of water consumption strategies.

To facilitate the calculation of the salvage value, the present value can be calculated as below.

$$PV = \sum_{k=1}^{13} PV(QOL_s^k) + \sum_{k=1}^{11} PV(LD_s^k) + \sum_{k=1}^{13} PV(RA_s^k) + \sum_{k=1}^{13} PV(NW_s^k) + \sum_{k=1}^{3} PV(CL_s^k) + \sum_{k=1}^{7} PV(EC_s^k) + \sum_{k=1}^{2} PV(WC_s^k) + \sum_{k=1}^{3} PV(Mat_s^k) + \sum_{k=1}^{6} PV(WM_s^k) \quad (47)$$

Here PV represents the present value; PV(QOL) means present value as a function of quality-of-life strategies.

GHG emissions objective function

The GHG emissions objective function attempts to minimize the emissions due to adoption of strategies under each of the nine decision variables.

$$Min\ GHGE(S) = \sum_{k=1}^{13} E(RA_s^k) + \sum_{k=1}^{13} E(NW_s^k) + \sum_{k=1}^{3} E(CL_s^k) + \sum_{k=1}^{7} E(EC_s^k) + \sum_{k=1}^{2} E(WC_s^k) + \sum_{k=1}^{3} E(Mat_s^k) + \sum_{k=1}^{6} E(WM_s^k) \quad (48)$$

The GHG emissions as a function of strategies need to be minimized and is expressed as the total emissions associated with the strategies under each of the associated decision variables.

Approach 1 – combining objectives

$$Max\ FitFunc = (W_1 \times SS) + (W_2 \times EnvS) - (W_3 \times LCC) - (W_4 \times GHGE) \quad (49)$$

The above equation uses weighted aggregation of various objectives to maximize the total value. In Equation (49), W_1, W_2, W_3, and W_4 correspond to the weights wherein these values vary between 0 and 1. By varying the weights between 0 and 1, a pareto front can be obtained which represents a set of non-dominated solutions. The variation of the weights can be mathematically represented on a hyperplane as the weight vector will always have a cardinality less than that of the objectives vector (Messac, 2015). The model has been kept flexible to provide the option for the user to enter the weights which correspond to the variables' relative importance.

Approach 2 – separating objectives

This approach uses a multiobjective approach which has been described in 3.3.4 Task 4: Implementation of optimization model.

3.3.3 Task 3: Definition of model constraints

Several constraints have been defined in this model to mimic the real-world expectations and constraints – (1) GHG emission threshold constraint, (2) budget constraint, (3) level of sustainability, (4) level of social sustainability, and (5) level of environmental sustainability.

Constraint 1 – GHG emissions

According to APTA SUDS-CC-RP (2009), the public transportation emissions are usually in a range of 0.12 to 1.2 lbs. of CO_2 per mile. Using this information, the GHG emissions threshold constraint for this model has been shown in **Error! Reference source not found.**.

$$\frac{Total\ GHGE}{Total\ mileage} \leq 1.2\ lbs\ CO_2 \qquad (50)$$

Constraint 2 - Budget

The budget constraint will be defined by the user/owner entity, and it will serve as an upper limit for the total initial cost (first cost).

$$\sum_{n=1}^{9} \chi_o \leq Budget \qquad (51)$$

Constraint 3 – Level of sustainability

The minimum level of overall sustainability has been derived from the lowest certification level in the ENVISION rating system, which is the verified level, and is awarded when a project attains 20% of the total points. Since this phase is accounting for just the sustainability categories and credits, the total points under this phase are 874 points. The overall minimum level of sustainability can be defined by the following equation.

$$LOS \geq 175\, points \qquad (52)$$

Constraint 4 – Level of social sustainability

To determine the lowest level of social sustainability, the credits under social sustainability were prioritized. Priorities were calculated based on the total points which make up each credit. Based on the relevance of credits to broader transportation sector, a few credits were chosen to determine the minimum level of social sustainability. Thresholds for each of these credits have been determined using the lowest level of achievement (LOA) based on the ENVISION rating system.

$$QL1.1 \geq 2 \qquad (53)$$

This equation signifies that the "improve community quality of life (QL1.1)" needs to have an improved or greater LOA.

$$QL1.2 \geq 2 \qquad (54)$$

This equation signifies that "enhance public health and safety (QL1.2)" needs to have an improved or greater LOA.

$$QL3.1 \geq 3 \qquad (55)$$

This equation signifies that "advance equity and social justice (QL3.1)" needs to have an improved or greater LOA.

Constraint 5 – Level of environmental sustainability

To determine the lowest level of environmental sustainability, the credits under environmental sustainability were prioritized. Priorities were calculated based on the total points which make up each credit. Based on the relevance of credits to broader transportation sector, a few credits were chosen to determine the minimum level of environmental sustainability. Thresholds for each of these credits have been determined using the lowest level of achievement (LOA) based on the ENVISION rating system.

$$CR1.2 \geq 8 \qquad (56)$$

This equation signifies that the "reduce greenhouse gas emissions (CR1.2)" needs to have an improved or greater LOA.

3.3.4 Task 4: Implementation of optimization model

In this optimization model, the objective functions are applied to dataset and feasible solutions are found based on a set of constraints. The model starts with definition of the input dataset(s) for each one of the decision variables as described above. Thereafter, the model uses Linear Programming as the base algorithm and applies the objective functions defined above to maximize social and environmental sustainability and minimize the greenhouse gas (GHG) emissions and life cycle cost (LCC). Lastly, the model finds the optimal solution (or set of optimal solutions) while exploring the computational time to reach the optimal.

A graphical representation of the implementation of the optimization model has been shown in Figure 20.

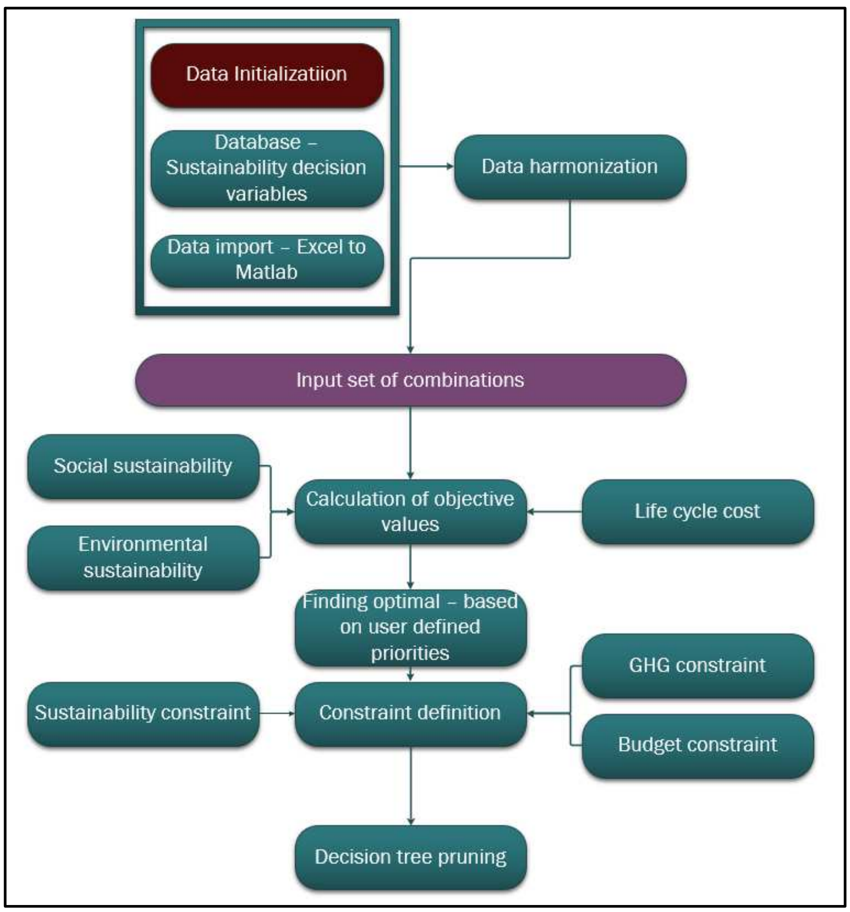

Figure 20: Flow of higher-level sustainability optimization process

As shown in Figure 20, the search for an optimal solution starts with data initialization through an excel-based dataset. It consists of details pertaining to each of the major objectives such as social sustainability, environmental sustainability, life cycle cost (LCC), and greenhouse gas emissions (GHG) for several strategies under each of the nine decision variables. This dataset is subject to frequent addition by users to ensure the comprehensiveness and adaptability of the dataset to various regions depending on the location of a project. Naming convention for the column headings and variable names have been kept consistent for easy understanding of any user or programmer. The excel-based dataset for all decision variables is imported into MATLAB which completes the data initialization process.

Data harmonization consists of appropriately categorizing the imported data into each of the sub-decision variables. For instance, the data for quality-of-life category under ENVISION that contributes to social sustainability contains all relevant strategies for each of the associated credits. To ensure that only one strategy is selected for every credit, this data needs to be categorized as per the quality-of-life credits. The same process is applied to the leadership category and the rest of the decision variables (resource allocation, natural world, climate, energy consumption, water consumption, materials, and waste management).

The constraints are defined in the MATLAB and are used to prune the search space. Since the level of social sustainability and environmental sustainability contain a minimum points constraint for improving community quality of life (QL1.1), enhance public health and safety (QL1.2), advance equity and social justice (QL3.1), and reduce greenhouse gas emissions (CR1.2), pruning will help reduce the search space when a large data inventory is being input. This can significantly reduce the computational time to find the optimal solution.

One strategy from each sub-decision variable is chosen that helps create a set of combinations. Each of these combinations represent potential solutions to our optimization problem. These combination sets are pruned further by eliminating the combinations which have a total cost greater than the user-specified budget. Though linear programming would have been the best algorithm for solving our optimization problem as both the objective function and all associated constraints are linear, however, the decision variables in our research only take discrete values. Therefore, linear programming cannot be used in this case as it takes discrete values for decision variables (Martinich, 2008; University of Kentucky, 2015). In the realm of discrete optimization, the problems are further broken down into five major categories (Messac, 2015):

1. Pure integer programming problems: this problem type is applied when the decision variables can only take integer values.
2. Mixed-integer programming problems: this problem type is applied when the decision variables can take a mixture of integer and continuous values.
3. Discrete non-integer problems: this problem type is applicable to scenarios where we have a discrete input dataset.
4. Binary programming problems: this problem type is applicable to scenarios where decision variables can only take values zero or one.
5. Combinatorial optimization problems: this problem type is applicable to scenarios where "the feasible solutions are defined by a combinatorial set resulting from the given feasible discrete values" of the decision variables.

The decision variables in this research are discrete and potential solutions would represent a combination of different feasible values, a combinatorial optimization is suitable for solving the optimization problem proposed in this phase. Furthermore, because the variables in this research are discrete and they represent an unordered state space which validates the usage of combinatorial optimization using heuristic methods (Arsham, 2015; Messac, 2015).

As discussed in **3.3.2 Task 2: Development of objective functions**, various objectives in this optimization problem can either be combined or kept separate. Weighted sum model, linear programming with relaxation approach, and branch and bound are a few classical optimization techniques which can be applicable to the scenario where objectives are combined. The weighted sum model is one of the easiest techniques to apply and it uses the exhaustive search to search for the optimal in the state space (space that graphically defines the position of optimal solution(s)). Since this technique uses an exhaustive search, its application becomes tedious due to the size of the model's dataset being exponential (Messac, 2015). In the linear programming with a relaxation approach, the problem is assumed as continuous, and the optimal solution is rounded off to the nearest feasible solution. However, in our optimization model, the set of potential combinations would need to be calculated to gauge the value in the discrete dataset that has the least distance to the assessed optimal. Therefore, it diminishes the use of this relaxation technique due to the need of calculation of objective values through an exhaustive approach. The branch and bound technique use the relaxation approach as the underlying algorithm, and therefore it has not been used for optimization for the same reason. In addition to the discussed limitations, these techniques will result in one optimal solution at the end of each simulation.

Usage of evolutionary approaches like genetic algorithm, simulated annealing, particle swarm optimization, and ant colony optimization among many others is recommended for the combinatorial optimization problem portrayed in this phase. These techniques explore numerous non-dominated solutions in just one simulation, thus reducing the computing time (Savic, 2002; Srinivas & Deb, 1994). The most widely applicable and robust evolutionary technique is the genetic algorithm (GA), and therefore, it has been used to find a set of optimal solutions for the sustainability optimization model (Abdallah & El-Rayes, 2016; Brunelli et al., 2016; Hashim et al., 2017; Rasi & Sohanian, 2020; Savic, 2002; Srinivas & Deb, 1994). This research uses the non-dominated sorting genetic algorithm (NSGA-II) to find the pareto set of optimal solutions for the various objectives detailed in **Task 2**. In this algorithm, first an initial population is generated which consists of a fixed number of chromosomes. These chromosomes denote the potential solutions (or combination of strategies) to achieve the different objectives. First the mutation and crossover operations of the genetic algorithm (GA) are applied to the initial population (also known as the parent population, Pt) and several children are generated to form the child population (Qt). These two GA operations have been described below.

A summary of the NSGA-II methodology detailed above, has been represented in Figure 21.

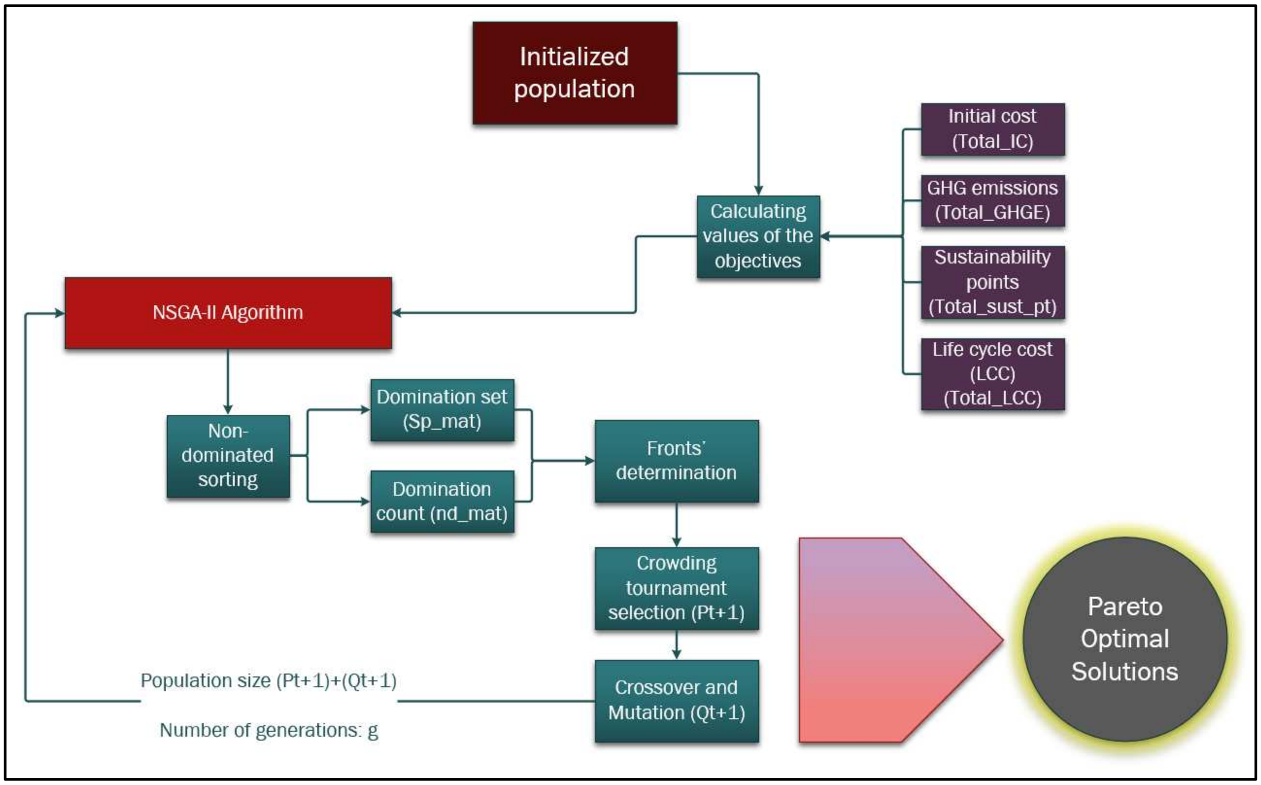

Figure 21: NSGA-II methodology (sustainability)

As shown in Figure 21, the initialized population is generated in the first step. Hereafter, the values of each of the objectives are calculated for each member of the combined population. The crossover and mutation portions, combined, are also known as Genetic Algorithm (GA). The NSGA-II algorithm follows the objectives' calculation, starting with the non-dominated sorting. The fronts are determined using the domination counts and another parent population is created after applying the crowding tournament selection operator. Crossover and mutation ensue, and the child populations are combined with the parent population. The entire process is repeated for a pre-defined number of generations, referred to as "g" in the code. At the end of "g" generations, the pareto optimal solutions are found. This pareto optimal is subjected to the list of constraints defined above using a decision tree pruning approach (Soldoozy et al., 2019). This approach helps to omit the solutions which do not follow the constraints. User's and decision maker's input is essential in any transportation project. The user defined priorities for the objectives are combined to determine fitness values of each of the remaining pareto solutions and the highest fitness solution is recommended to the user or decision maker. The fitness function has been shown in Equation (58).

$$Fitfunc = \frac{w1.(Initial\ Cost)}{(w1+w2+w3+w4)} + \frac{w2.(LCC)}{(w1+w2+w3+w4)} + \frac{w3.(GHGE)}{(w1+w2+w3+w4)} + \frac{w4.(Sust.points)}{(w1+w2+w3+w4)} \qquad (57)$$

Each of the components of the NSGA-II have been explained below. In the crossover operation, two parents are selected, and two child members are created. In the crossover operation, two parents are selected, and two child members are created. For this purpose, a uniform crossover approach was selected by creating a binary array that has the same length as each of the parent chromosomes. If the randomly generated value of the binary variable is zero, then Parent 1's array value is selected, or else if the binary variable is 1, then the Parent 2's array value is selected (Hassanat et al., 2019). This concept has been well represented in Table 7.

Table 7: Crossover representation

Parent 1	1	2	3	.	.	.	7	8	9	10
Parent 2	11	12	13	.	.	.	17	18	19	20
Binary variable	1	0	1	.	.	.	1	0	0	1
Child 1	11	2	13	.	.	.	17	8	9	20
Child 2	1	12	3	.	.	.	7	18	19	10

After crossover, the parent population goes under mutation to create children population. In this case, a mutation rate array is generated randomly, having same size as any of the parent chromosomes. Thereafter, a mutation rate is defined which serves as the upper threshold for mutation. Mutation takes place at all indices where the randomly generated mutation rate is less than this "defined" mutation rate. A depiction of this concept has been shown in Table 8.

Table 8: Mutation representation

Parent 1	1	2	3	.	.	.	7	8	9	10
Parent 2	11	12	13	.	.	.	17	18	19	20
Mutation rates	0.1	0.2	0.001	.	.	.	0.03	0.05	0.5	0.9
Child 1	1	2	23	.	.	.	27	28	9	10
Child 2	11	12	33	.	.	.	37	38	19	20

The crossover and mutation operations, each, generate a child population of the same size as the initial parent population. For example, if the initial parent population is of size N, then the total population (parents, Pt plus all children, Qt from crossover and mutation) will be of size 3N.

This entire population (Pt + Qt) serves as the input for the NSGA-II algorithm. It starts with the concept of domination check wherein each potential solution (also known as the chromosome) is tested to see which solutions it dominates and by which solutions is it dominated. For one solution to dominate the second, the following conditions should be met (Deb, 2001; Srinivas & Deb, 1994):

1. The first solution should be no worse than the second solution in all the objectives
2. The first solution should be strictly better than the second solution in at least one of the objectives

To understand the concept of domination and represent the above conditions mathematically, consider an example of two objectives that need to be minimized. Let objective 1 be represented by X and objective 2 be represented by Y. For potential solutions S1 and S2, let x1 and x2 be the respective values for the objective 1, and y1 and y2 be the respective values for objective 2. For a solution S1 to dominate S2 (S1<S2), the following criteria should be satisfied:

$[(x1 \leq x2) \ \& \ (y1 \leq y2)] \ \& \ [(x1 < x2) \text{ OR } (y1 < y2)]$

For the members in the population Pt + Qt, the above domination check is exercised, and a domination count and domination set are determined for each member of the total population (Pt + Qt). Consider an individual solution (or individual chromosome) S1. Domination count denotes the number of total solutions that dominate this individual S1. Domination set on the other hand refers to the list of individuals that this solution (S1) dominates. To achieve this in the MATLAB code, a nested for-loop was created, and two arrays were created which represented the domination count and domination set for each member of the population. In a traditional non-dominated sorting, the fronts are created while the domination set, and domination counts are being calculated. This traditional non-dominated sorting approach has been shown in Figure 22.

for each $p \in P$	
$S_p = \emptyset$	
$n_p = 0$	
for each $q \in P$	
if $(p \prec q)$ then	If p dominates q
$S_p = S_p \cup \{q\}$	Add q to the set of solutions dominated by p
else if $(q \prec p)$ then	
$n_p = n_p + 1$	Increment the domination counter of p
if $n_p = 0$ then	p belongs to the first front
$p_{\mathrm{rank}} = 1$	
$\mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}$	
$i = 1$	Initialize the front counter
while $\mathcal{F}_i \neq \emptyset$	
$Q = \emptyset$	Used to store the members of the next front
for each $p \in \mathcal{F}_i$	
for each $q \in S_p$	
$n_q = n_q - 1$	
if $n_q = 0$ then	q belongs to the next front
$q_{\mathrm{rank}} = i + 1$	
$Q = Q \cup \{q\}$	
$i = i + 1$	
$\mathcal{F}_i = Q$	

Figure 22: Non dominated sorting approach (Srinivas & Deb, 1994)

However, this approach has been modified in this research to create all the fronts in one step. To understand this modified approach, an example has been mentioned below.

Consider the below plotted points (1 through 5) for two objectives as shown in Figure 23. F1 on the x axis needs to be maximized and F2 on the y axis needs to be minimized.

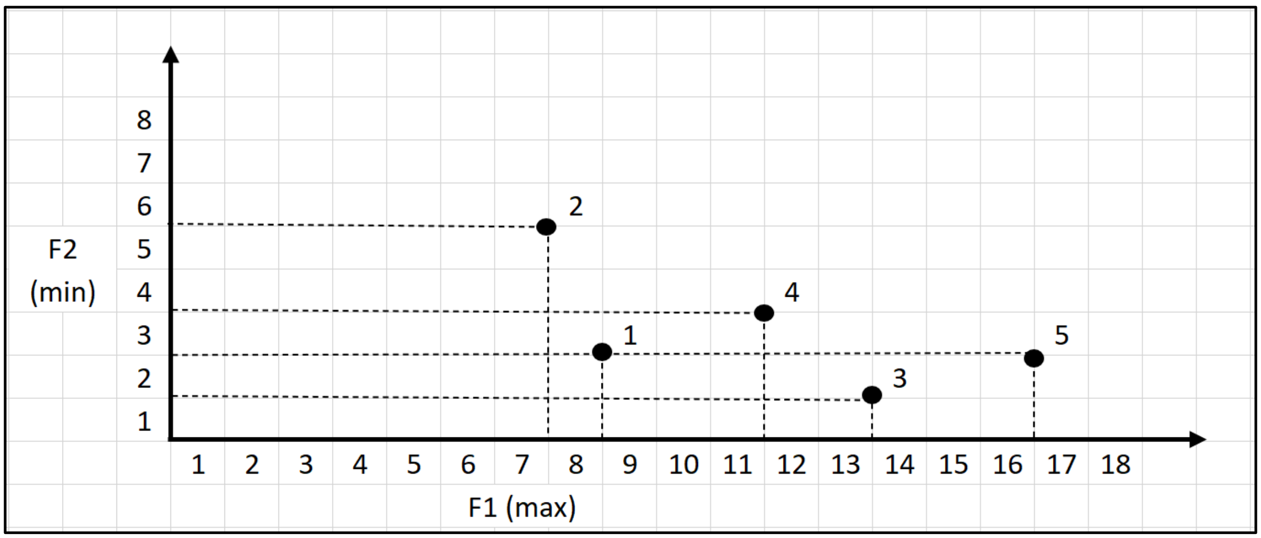

Figure 23: Example to understand modified front calculation

Using the traditional non-dominated sorting approach (Deb, 2001), the various fronts have been shown in Table 9.

Table 9: Fronts from traditional non-dominated sorting

Front 1	3	5
Front 2	1	4
Front 3	2	

In this research, the domination counts have been used to calculate the various fronts. The domination counts of each of the points mentioned in Figure 23 have been elaborated in Table 10.

Table 10: Domination counts of the solutions

Potential solutions	Domination counts
1	2
2	4
3	0
4	2
5	0

These domination counts are sorted in ascending order and the potential solutions having the same count are categorized in the same front. Solutions having domination counts as zero are categorized under Front 1, solutions having domination count as one are categorized under Front 2, and so on. It can be observed that following this process categorizes solutions 3 and 5 under Front 1, solutions 1 and 4 under Front 2, and solution 2 under Front 3. This modification eliminates the need to use a while loop, thereby making the MATLAB code more user-friendly and devoid of the risk of running an infinite loop (Horvat, 2018). Hereafter, a crowding tournament selection is used.

A crowding tournament selection operation is used to filter elite members from the various fronts as categorized using the non-dominated sorting. The crowded tournament selection operation contains two important conditions:

1. Solutions from the higher fronts is selected first
2. If two solutions belong to the same front, then crowding distance is calculated and the solution with a lower crowding distance is selected

The crowding distance calculation is done for every objective. First the potential solutions are sorted in ascending order for each of the objectives. Thereafter Equation 18 is applied to calculate the crowding distance for each of the solutions under each of the objectives.

$$I[i] = I[i] + \left(\frac{I[i+1].m - I[i-1].m}{f_m^{max} - f_m^{min}}\right) \qquad (58)$$

The crossover and mutation operations are applied to the filtered elite members, after which the non-dominated sorting and crowding distance calculation ensues. This process is repeated for a user-defined number of generations. The output of this optimization model provides an optimal solution based on the user defined priorities.

3.3.5 Task 5: Model application – case study

The case study used in this research is a highway project in Colorado which was constructed in 2020 and managed by Colorado Department of Transportation (CDOT). As there are no ENVISION certified roads and highway projects in Colorado at the time of this research study, the CDOT project mentioned above was undertaken for the purpose of case study and several sustainable initiatives were introduces for the ENVISION rating system to be applicable. Thereafter, the sustainability optimization model was used to select the strategies which can help to achieve the highest level of sustainability while ensuring that the life cycle cost, and greenhouse gas (GHG) emissions are minimized. Figure 24 shows a map of different highways which were part of a bigger CDOT project. One of these highways is the State Highway 71 South of Limon which this research used as a case study.

The total project cost was $16,679,000 and it did not contain any of the sustainable and resilient measures as part of the ENVISION rating system. Data was collected for other road and highway projects that helped to create this case study with sustainability and resilience attributes. The following sources were used for data –

1. ENVISION documentation: this provided a list of ENVISION categories and credits, and the exact steps to achieve the credits. It also provided a few examples of strategies that could be used to target the different categories in ENVISION.

2. Walsh's Ohio River Bridges Project: this project targeted the categories namely, quality of life, leadership, and climate and resilience. Therefore, they targeted both the sustainability and resilience credits. The strategies used in this project were customized for the above case study.
3. Interstate 4 Ultimate Project in Florida: this was one of the biggest roads and highway projects certified under the ENVISION rating system. Due to confidentiality clause of the project and the data collection process happening during the peak of COVID, only the data for Natural world and Resource allocation could be obtained which helped to customize strategies for the above case study.
4. Third party verifiers: several verifiers were contacted to share the data related to roads and highways certification through the ENVISION rating system. Though specific project data could not be obtained, it provided a plethora of information about the level of achievement under each category for various road and highway projects.

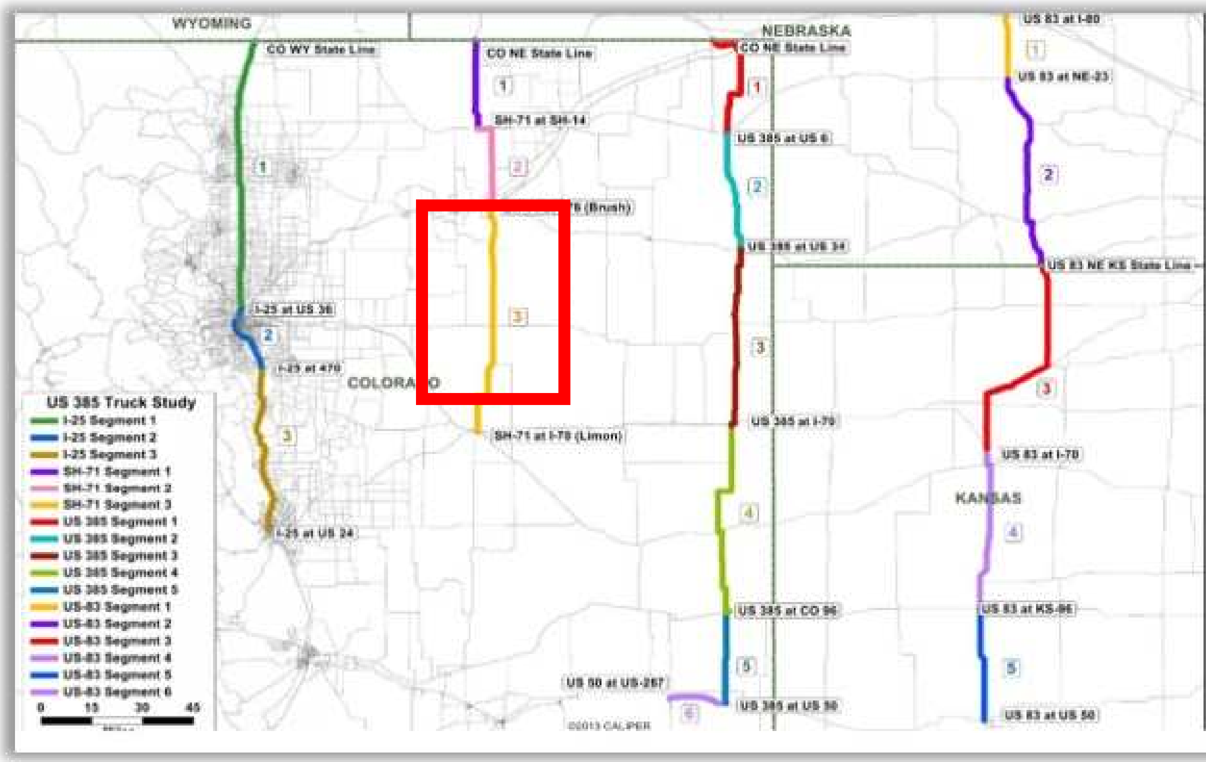

Figure 24: Case study SH 71 (south of Limon)

In addition to the data from different sources described above, the Road Emissions Model was used to quantify the emissions associated with carious inputs through the planning, design, construction, and operation and maintenance phase of the project. Vendors associated with transportation projects were referenced for the associated cost of materials, equipment, or process.

3.4 Phase 3: Resilience optimization model

This phase was aimed at creation of a resilience optimization model which involves solving the tradeoff between resilience (and its dimensions), and the life cycle cost (LCC). Resilience has been considered as per definition in the ENVISION rating system. The institute of sustainable infrastructure (ISI) proposes using ENVISION framework for measuring the sustainability of infrastructure projects. Figure 25 details the methodology adopted to create the resilience optimization model.

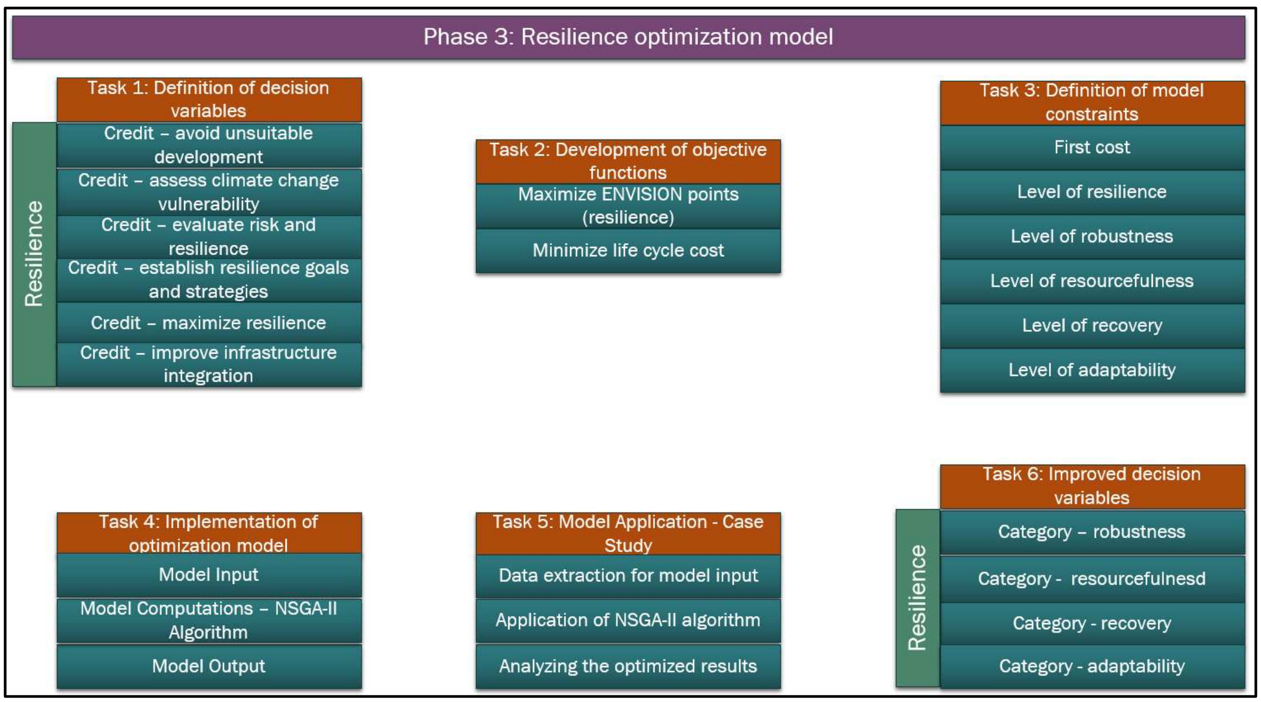

Figure 25: Resilience optimization model

For this resilience optimization model, the decision variables are defined first and then the various objective functions are detailed. The constraints are defined and are applied when the optimization model is implemented through an example case study. This phase uses the ENVISION rating system's resilience section as the basis of the decision variables. ENVISION does not define the various dimensions of resilience, and therefore this research also proposes several dimensions of resilience and the credits within those dimensions. These credits can be used in an improved optimization model for future research.

3.4.1 Task 1: Definition of decision variables

There is one category for resilience under the ENVISION rating system which consists of six credits. These credits assist in obtaining different number of points that define the level of achievement for each credit, thereby defining the level of resilience for any transportation project.

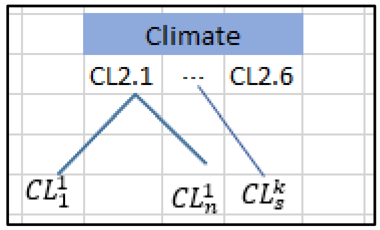

Figure 26: Decision variables derived from ENVISION – resilience

Decision variables for the climate category have been defined as CL_s^k wherein 'k' signifies each of the credits under the climate category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 6 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, CL_1^1 means that for CR2.1 credit (Avoid unsuitable development), strategy I has been selected which reduces the net embodied carbon over the life cycle of a transportation project by accounting for raw material and its transportation to project site. Figure 26 provides a visual representation of decision variables based on the ENVISION rating system.

Furthermore, other decision variables which help achieve points in the ENVISION rating system have been shown in Figure 27.

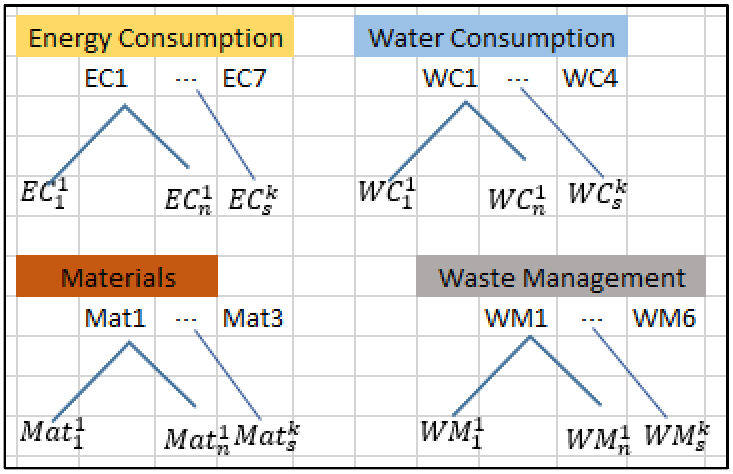

Figure 27: Other decision variables driving resilience

The energy consumption decision variable has been defined as EC_s^k wherein 'k' signifies the various sources of energy consumption in this model namely, trucks for transportation, compaction equipment, soil stabilization equipment, dozers and graders, scrapers, excavators, and street lighting (Peurifoy et al., 2018). 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 7 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, EC_1^1 means that for EC1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The water consumption decision variable has been defined as WC_s^k wherein 'k' signifies the various sources of water consumption in this model (predominantly in road median landscaping) namely, sprinkler system, water sprinkled by water trucks etc. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 2 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WC_1^1 means that for WC1 (sprinkler system), strategy I has been selected which signifies one of the alternatives of sprinkler system type.

The materials decision variable has been defined as Mat_s^k wherein 'k' signifies the major materials which have the highest share of the total cost namely, asphalt, concrete, and excavation and backfill. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 3 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, Mat_1^1 means that for Mat1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The waste management decision variable has been defined as WM_s^k wherein 'k' signifies the various sources of waste management in this model namely, waste reduction, reuse/recycle on site, materials sent to recycling facilities, materials sent to manufacturer, composting, and materials sent to landfills. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 6 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WM_1^1 means that for WM1 (waste reduction), strategy I has been selected which signifies one of the alternatives for waste reduction.

3.4.2 Task 2: Development of objective functions

The objective functions are developed to address the tradeoffs defined above for phase **2**. These siloed objective functions help achieve – (1) maximization of points associated with each of the ENVISION credits under resilience, (2) minimization of life cycle cost (LCC), and (4) minimization of the GHG emissions.

Resilience objective function

The resilience objective function attempts to maximize the number of points associated with resilience category in the ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ RL(S) = \sum_{k=1}^{6} Pts(CL_s^k) + \sum_{k=1}^{7} Pts(EC_s^k) + \sum_{k=1}^{2} Pts(WC_s^k) + \sum_{k=1}^{3} Pts(Mat_s^k) + \sum_{k=1}^{6} Pts(WM_s^k) \qquad (59)$$

In Equation (59), resilience is calculated as a function of strategies under each of the credits under the resilience category of ENVISION. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's resilience points. These points are added together to find the level of social sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 28.

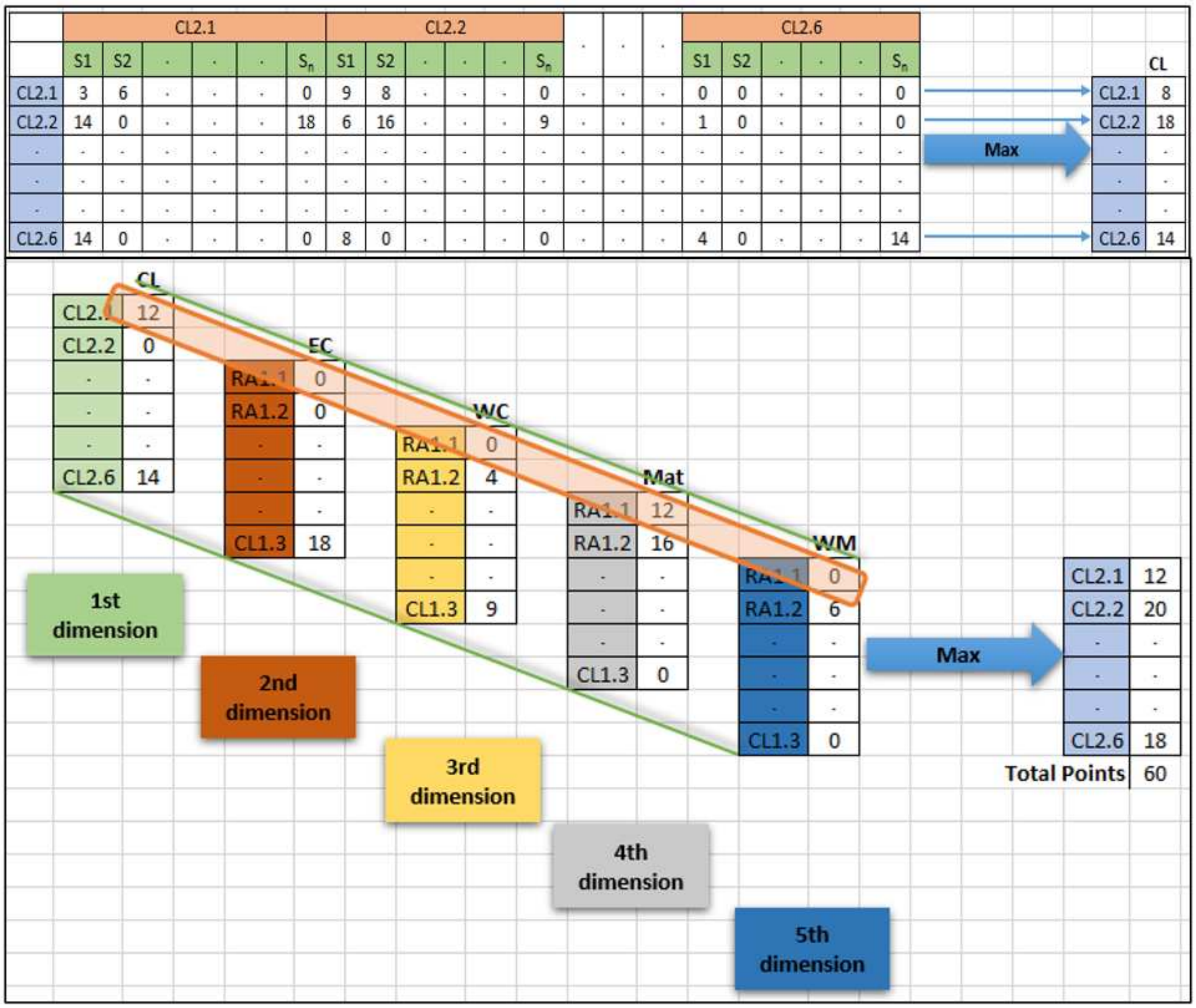

Figure 28: Points calculation methodology – Resilience

As shown in Figure 28, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (59)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the five main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (59). Thus, in this case, we have five dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with resilience need to be maximized.

Life cycle cost objective function

The life cycle cost (LCC) objective function attempts to minimize the life cycle cost associated with the strategies adopted within the five decision variables (Scheving, 2011; Sompura & Avetisyan, 2017).

$$Min\ LCC(S) = \chi_o + \left\{\sum_{n=1}^{LC/15} \frac{Y}{(1+i)^{15n}} + \sum_{n=1}^{LC/5} \frac{Z}{(1+i)^{5n}}\right\} - \frac{S}{(1+i)^N} \quad (60)$$

$$S = P - (Annual\ Depreciation \times Useful\ life) \qquad (61)$$

Here χ_o refers to the initial cost (or first cost) of the strategies as described in Equation (44). The computation inside curly brackets corresponds to the operations and maintenance phase. It consists of rehabilitation cost (variable Y) signifying the maintenance, and street lighting and water consumption costs (variable Z) signifying the operations. It has been determined that the rehabilitation of a road projects should be done every 15 years on an average and the maintenance activities are usually done every five years (Portland Bureau of Transportation, 2021). Therefore, the values for variable Y have been calculated and added together, after every 15 years throughout the life cycle; values for variable Z have been calculated and added together after every five years throughout the life cycle. Variable S determines the salvage value as defined in Equation (42).

$$\chi_o = \sum_{k=1}^{6} IC(CL_s^k) + \sum_{k=1}^{7} IC(EC_s^k) + \sum_{k=1}^{2} IC(WC_s^k) + \sum_{k=1}^{3} IC(Mat_s^k) + \sum_{k=1}^{6} IC(WM_s^k) \quad (62)$$

Here IC represents the initial cost; IC(CL) means initial cost as a function of resilience strategies.

$$Y = \sum_{k=1}^{7} RC(EC_s^k) + \sum_{k=1}^{2} RC(WC_s^k) + \sum_{k=1}^{3} RC(Mat_s^k) \qquad (63)$$

RC represents the rehabilitation cost; RC(EC) means rehabilitation cost as a function of energy consumption strategies.

$$Z = \sum_{k=1}^{7} OC(EC_s^k) + \sum_{k=1}^{2} OC(WC_s^k) \quad (64)$$

OC signifies the operations cost; OC(EC) signifies the operating cost of street lighting throughout the life cycle of the project. OC(WC) means operating cost as a function of water consumption strategies.

To facilitate the calculation of the salvage value, the present value can be calculated as below.

$$PV = \sum_{k=1}^{6} PV(CL_s^k) + \sum_{k=1}^{7} PV(EC_s^k) + \sum_{k=1}^{2} PV(WC_s^k) + \sum_{k=1}^{3} PV(Mat_s^k) + \sum_{k=1}^{6} PV(WM_s^k)$$

(65)

Here PV represents the present value; PV(CL) means present value as a function of resilience strategies.

GHG emissions objective function

The GHG emissions objective function attempts to minimize the emissions due to adoption of strategies under each of the nine decision variables.

$$Min\ GHGE(S) = \sum_{k=1}^{6} E(CL_s^k) + \sum_{k=1}^{7} E(EC_s^k) + \sum_{k=1}^{2} E(WC_s^k) + \sum_{k=1}^{3} E(Mat_s^k) + \sum_{k=1}^{6} E(WM_s^k)$$

(66)

The GHG emissions as a function of strategies need to be minimized and is expressed as the total emissions associated with the strategies under each of the associated decision variables.

Approach 1 – combining objectives

$$Max\ FitFunc = (W_1 \times Res) - (W_2 \times LCC) - (W_3 \times GHGE) \quad (67)$$

The above equation uses weighted aggregation of various objectives to maximize the total value. In Equation (67), W_1, W_2, and W_3, correspond to the weights wherein these values vary between 0 and 1. By varying the weights between 0 and 1, a pareto front can be obtained which represents a set of non-dominated solutions. The variation of the weights can be mathematically represented on a hyperplane as the weight vector will always have a cardinality less than that of the objectives vector (Messac, 2015). The model has been kept flexible to provide the option for the user to enter the weights which correspond to the variables' relative importance.

Approach 2 – separating objectives

This approach uses a multiobjective approach which has been described in 3.3.4 Task 4: Implementation of optimization model.

3.4.3 Task 3: Definition of model constraints

Several constraints have been defined in this model to mimic the real-world expectations and constraints – (1) GHG emissions threshold constraint, (2) budget constraint, and (3) level of resilience.

The constraint for GHG emissions and budget is the same as defined in section 3.3.3 Task 3: Definition of model constraints.

Constraint 3 – Level of resilience

The minimum level of overall resilience has been derived from the lowest certification level in the ENVISION rating system, which is the verified level, and is awarded when a project attains 20% of the total points. Since this phase is accounting for just the sustainability categories and credits, the total points under this phase are 126 points. The overall minimum level of resilience can be defined by the following equation.

$$LOS \geq 25\, points \qquad (68)$$

3.4.4 Task 4: Implementation of optimization model

In this optimization model, the objective functions are applied to dataset and feasible solutions are found based on a set of constraints. The model starts with definition of the input dataset(s) for each one of the decision variables as described above. Thereafter, the model uses Linear Programming as the base algorithm and applies the objective functions defined above to maximize resilience and minimize the greenhouse gas (GHG) emissions and life cycle cost (LCC). Lastly, the model finds the optimal solution (or set of optimal solutions) while exploring the computational time to reach the optimal. A graphical representation of the implementation of the optimization model has been shown in Figure 29.

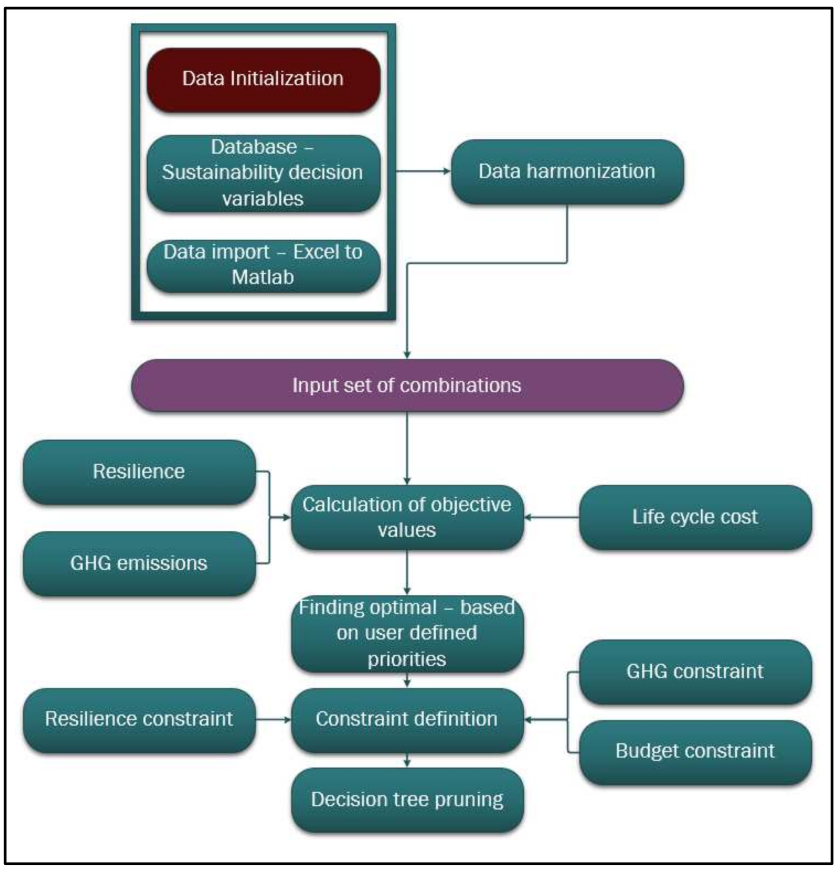

Figure 29: Flow of higher-level resilience optimization process

As shown in Figure 29, the search for an optimal solution starts with data initialization through an excel-based dataset. It consists of details pertaining to each of the major objectives such as resilience, life cycle cost (LCC), and greenhouse gas emissions (GHG) for several strategies under each of the nine decision variables. This dataset is subject to frequent addition by users to ensure the comprehensiveness and adaptability of the dataset to various regions depending on the location of a project. Naming convention for the column headings and variable names have been kept consistent for easy understanding of any user or programmer. The excel-based dataset for all decision variables is imported into MATLAB which completes the data initialization process.

Data harmonization consists of appropriately categorizing the imported data into each of the sub-decision variables. For instance, the "avoid unsuitable development" (CR 2.1) credit under ENVISION that contributes to resilience contains all relevant strategies to achieve pints under the credit CR 2.1. To ensure that only one strategy is selected for every credit, this data needs to be categorized as per the resilience credits.

The constraints are defined in the MATLAB and are used to prune the search space. Since the level of resilience contain a minimum points constraint for resilience, pruning will help reduce the search space when a large data inventory is being input. This can significantly reduce the computational time to find the optimal solution.

One strategy from each sub-decision variable is chosen that helps create a set of combinations. Each of these combinations represent potential solutions to our optimization problem. These combination sets are pruned further by eliminating the combinations which have a total cost greater than the user-specified budget. Though linear programming would have been the best algorithm for solving our optimization problem as both the objective function and all associated constraints are linear, however, the decision variables in our research only take discrete values. Therefore, linear programming cannot be used in this case as it takes discrete values for decision variables (Martinich, 2008; University of Kentucky, 2015). In the realm of discrete optimization, the problems are further broken down into five major categories (Messac, 2015):

1. Pure integer programming problems: this problem type is applied when the decision variables can only take integer values.
2. Mixed-integer programming problems: this problem type is applied when the decision variables can take a mixture of integer and continuous values.
3. Discrete non-integer problems: this problem type is applicable to scenarios where we have a discrete input dataset.
4. Binary programming problems: this problem type is applicable to scenarios where decision variables can only take values zero or one.
5. Combinatorial optimization problems: this problem type is applicable to scenarios where "the feasible solutions are defined by a combinatorial set resulting from the given feasible discrete values" of the decision variables.

The decision variables in this research are discrete and potential solutions would represent a combination of different feasible values, a combinatorial optimization is suitable for solving the optimization problem proposed in this phase. Furthermore, because the variables in this research are discrete and they represent an unordered state space which validates the usage of combinatorial optimization using heuristic methods (Arsham, 2015; Messac, 2015).

As discussed in 3.4.2 Task 2: Development of objective functions, various objectives in this optimization problem can either be combined or kept separate. Weighted sum model, linear programming with relaxation approach, and branch and bound are a few classical optimization techniques which can be applicable to the scenario where objectives are combined. The weighted sum model is one of the easiest techniques to apply and it uses the exhaustive search to search for the optimal in the state space (space that graphically defines the position of optimal solution(s)). Since this technique uses an exhaustive search, its application becomes tedious due to the size of the model's dataset being exponential (Messac, 2015). In the linear programming with a relaxation approach, the problem is assumed as continuous, and the optimal solution is rounded off to the nearest feasible solution. However, in our optimization model, the set of potential combinations would need to be calculated to gauge the value in the discrete dataset that has the least distance to the assessed optimal. Therefore, it diminishes the use of this relaxation technique due to the need of calculation of objective values through an exhaustive approach. The branch and bound technique use the relaxation approach as the underlying algorithm, and therefore it has not been used for optimization for the same reason. In addition to the discussed limitations, these techniques will result in one optimal solution at the end of each simulation.

Usage of evolutionary approaches like genetic algorithm, simulated annealing, particle swarm optimization, and ant colony optimization among many others is recommended for the combinatorial optimization problem portrayed in this phase. These techniques explore numerous non-dominated solutions in just one simulation, thus reducing the computing time (Savic, 2002; Srinivas & Deb, 1994). The most widely applicable and robust evolutionary technique is the genetic algorithm (GA), and therefore, it has been used to find a set of optimal solutions for the resilience optimization model (Abdallah & El-Rayes, 2016; Brunelli et al., 2016; Hashim et al., 2017; Rasi & Sohanian, 2020; Savic, 2002; Srinivas & Deb, 1994). This research uses the non-dominated sorting genetic algorithm (NSGA-II) to find the pareto set of optimal solutions for the various objectives detailed in **Task 2**. In this algorithm, first an initial population is generated which consists of a fixed number of chromosomes. These chromosomes denote the potential solutions (or combination of strategies) to achieve the different objectives. First the mutation and crossover operations of the genetic algorithm (GA) are applied to the initial population (also known as the parent population, Pt) and several children are generated to form the child population (Qt). These two GA operations have been described below.

A summary of the NSGA-II methodology detailed above, has been represented in Figure 30.

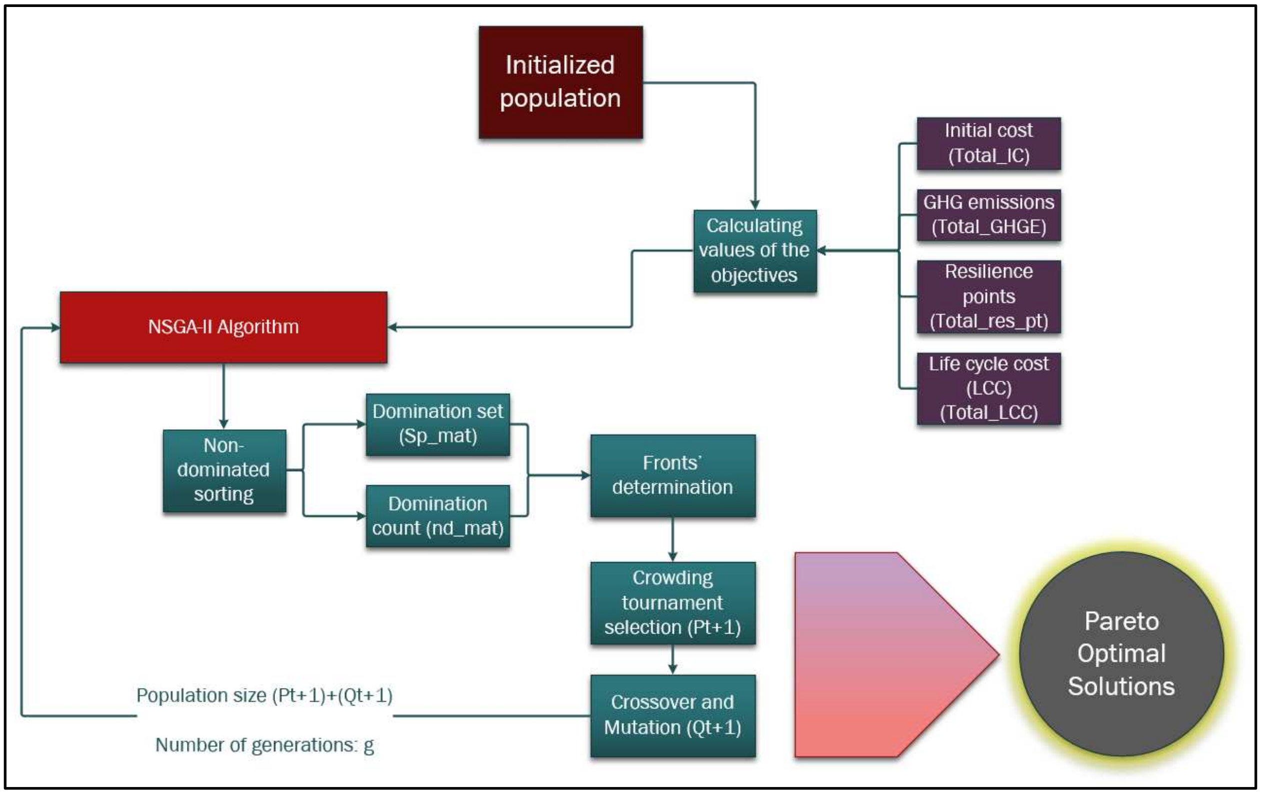

Figure 30: NSGA-II methodology (resilience)

The NSGA-II methodology remains same as defined in detail in 3.3.4 Task 4: Implementation of optimization model, with the only difference of the various objectives being input into the optimization model.

3.4.5 Task 5: Model application – case study

The case study used in this research is a highway project in Colorado which was constructed in 2020 and managed by Colorado Department of Transportation (CDOT). As there are no ENVISION certified roads and highway projects in Colorado at the time of the research study, the CDOT project mentioned above was undertaken for the purpose of case study and several resilient initiatives were introduced for the ENVISION rating system to be applicable. Thereafter, the resilience optimization model was used to select the strategies which can help to achieve the highest level of resilience while ensuring that the life cycle cost, and greenhouse gas (GHG) emissions are minimized.

3.4.6 Task 6: Improved decision variables

ENVISION is the most widely used infrastructure rating system in the United States (US), and the usage of its resilience credits to create the resilience optimization model aligns well with the sustainability and resilience standards created by the American Society of Civil Engineers (ASCE). Though the sustainability credits cover various aspects in detail, resilience credits are broad and leave much room for interpretation (and sometimes misinterpretation). Therefore, this research details several decision variables under each of the four dimensions of resilience, such as robustness, resourcefulness, recovery, and adaptability. Several rating systems apart from ENVISION, were reviewed, namely CEEQUAL, Greenroads, INVEST, I-LAST, and AGIC/IS. These systems provided a description of the resilience coverage which was combined with the quantification research published for each of the four dimensions to develop more indicators (can also be referred to as decision variables or credits).

3.5 Phase 4: Integrated sustainability-resilience optimization model

This phase was aimed at creating a sustainability and resilience optimization model which involves the tradeoff between sustainability (and its dimensions), resilience (and its dimensions), and the life cycle cost (LCC). The optimization models created in sections This phase has been divided into two parts; the first part is focused on conducting a comprehensive literature review, and the second part contains synthesizing the literature. The literature review was conducted systematically starting with a search for articles focusing on the state of the US infrastructure (especially the transportation infrastructure). Thereafter, sustainability and resilience definitions were explored and the various dimensions of each were analyzed. The quantification of sustainability and resilience was detailed, which mainly consisted of various assessment metrics (quantitative, qualitative, or mixed) or the application of various rating systems (ENVISION, CEEQUAL, AGIC/IS). In the second part, the gathered literature was analyzed and synthesized through a three-layered investigation. The differences between the definition of sustainability and resilience were observed. Thereafter, the differences between the dimensions of sustainability and resilience were understood. The interconnection between the broader concepts of sustainability and resilience and their dimensions was further examined. Hereafter, the measurement techniques for sustainability and resilience, and their associated dimensions was detailed to find the optimal measurement technique(s) for infrastructure projects.

3.3 Phase 2: Sustainability (triple bottom line) optimization model and

3.4 Phase 3: Resilience optimization model were combined to create an integrated optimization model for sustainability and resilience.

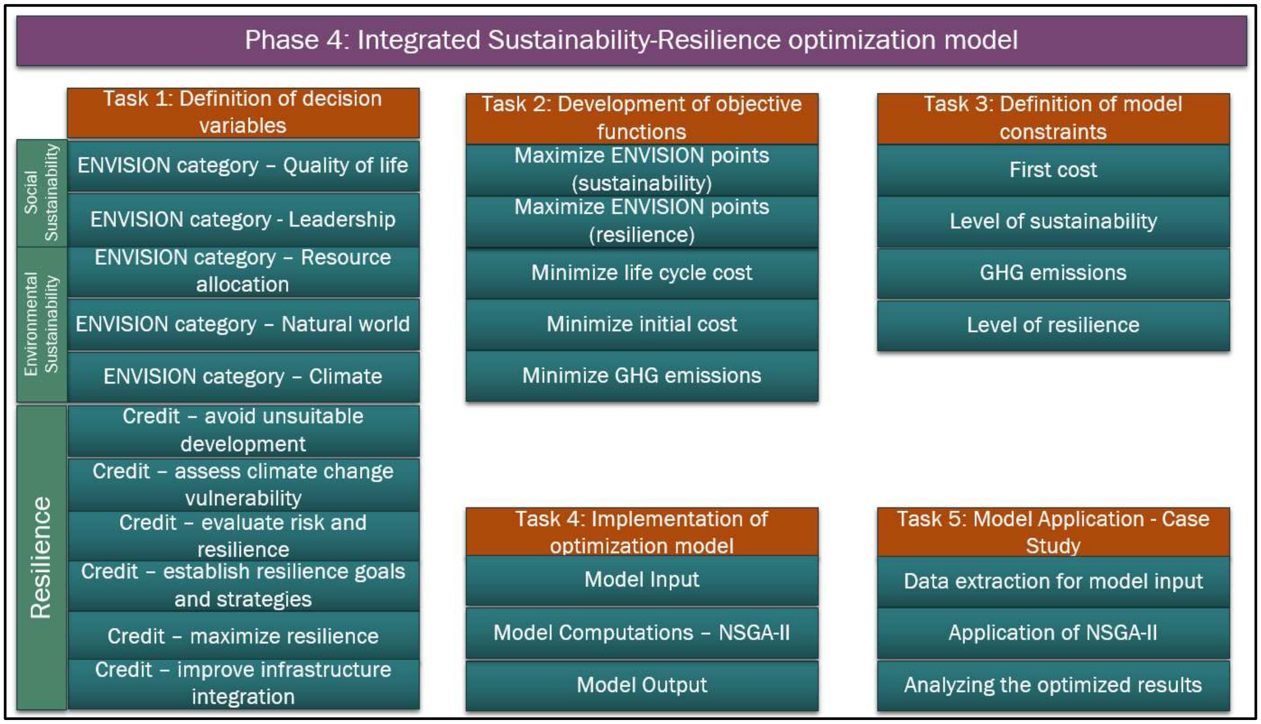

Figure 31: Integrated sustainability and resilience optimization model mapping

For this integrated sustainability and resilience optimization model, the decision variables are defined first and then the various objective functions are detailed. The constraints are defined and are applied when the optimization model is implemented through an example case study. This phase uses the ENVISION rating system's sustainability and resilience sections as the basis of the decision variables.

3.5.1 Task 1: Definition of decision variables

This task uses the decisions variables to represent feasible alternatives which was successfully implemented by Abdallah (2014), to represent different decision variables. These decision variables fall in multiple sustainability categories (quality of life, leadership, resource allocation, natural world, climate), Resilience category, energy consumption, water consumption, materials, and waste management. Credits under each of the categories assist in obtaining different number of points that define the level of achievement for each credit, thereby defining the level of sustainability and resilience for any transportation project. Figure 32 provides a visual representation of decision variables based on the ENVISION rating system.

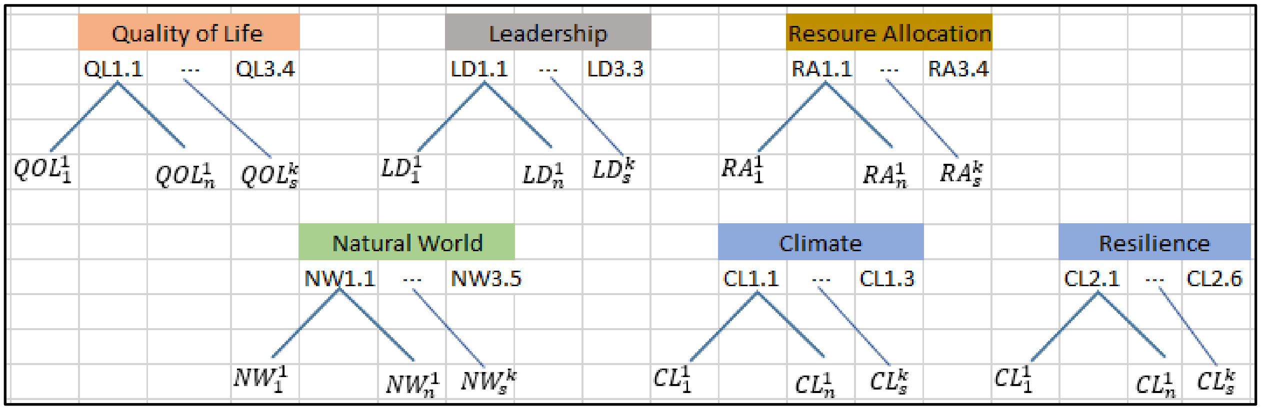

Figure 32: Decision variables derived from ENVISION

Figure 32 provides a graphical representation of five different decision variables as they relate to different ENVISION categories. Decision variables for the quality-of-life category have been defined as QOL_s^k wherein 'k' signifies each of the credits under the quality-of-life category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 13 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, QOL_2^3 means that for QL1.3 credit (Improve construction safety), strategy II has been selected which helps in improving the safety of public and workers on construction site for a transportation project.

Decision variables for the leadership category have been defined as LD_s^k wherein 'k' signifies each of the credits under the leadership category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 11 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, LD_3^1 means that for LD1.1 credit (Provide effective leadership and commitment), strategy III has been selected which promotes effective leadership and commitment in the project team to achieve the sustainability goals of a transportation project.

Decision variables for the resource allocation category have been defined as RA_s^k wherein 'k' signifies each of the credits under the resource allocation category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 13 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, RA_1^7 means that for RA2.2 credit (Reduce construction energy consumption), strategy I has been selected which reduces the total energy consumption to further result in reduction of greenhouse gas (GHGs) emissions and air pollutants during construction of a transportation project.

Decision variables for the natural world category have been defined as NW_s^k wherein 'k' signifies each of the credits under the natural world category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 13 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, NW_2^{11} means that for NW3.3 credit (Maintain floodplain functions), strategy II has been selected which helps maintain the floodplain functions by minimizing the development in or near a floodplain while executing a transportation project.

Decision variables for the climate category have been defined as CL_s^k wherein 'k' signifies each of the credits under the climate category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 3 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, CL_1^1 means that for CR1.1 credit (Reduce net embodied carbon), strategy I has been selected which reduces the net embodied carbon over the life cycle of a transportation project by accounting for raw material and its transportation to project site.

Decision variables for the resilience category have been defined as CL_s^k wherein 'k' signifies each of the credits under the climate category and 's' signifies the selection of one strategy (among various alternatives of strategies) to achieve the points for that credit. 'k' ranges from 1 to 6 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, CL_1^1 means that for CR2.1 credit (Avoid unsuitable development), strategy I has been selected which reduces the net embodied carbon over the life cycle of a transportation project by accounting for raw material and its transportation to project site.

Furthermore, other decision variables which help achieve points in the ENVISION rating system have been shown in Figure 33.

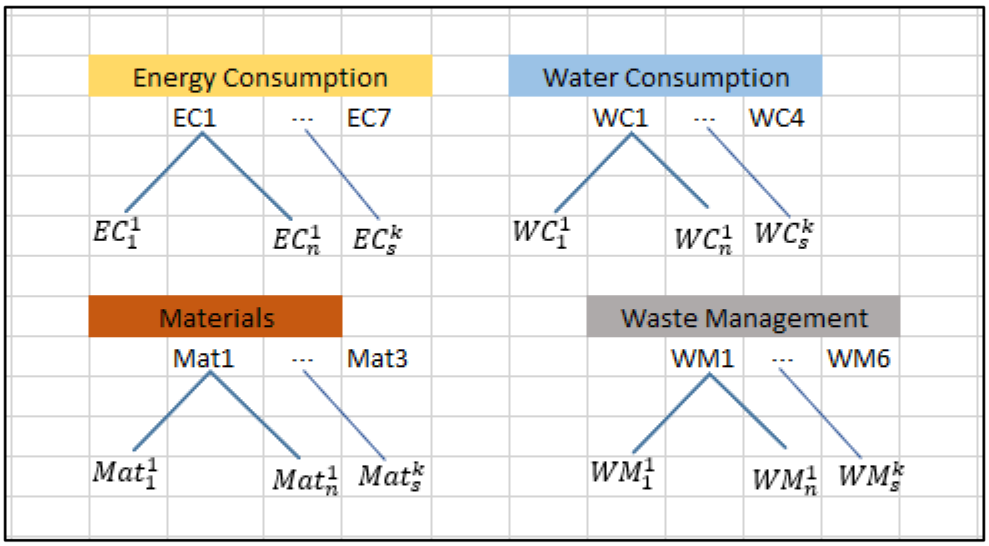

Figure 33: Other decision variables driving sustainability and resilience

The energy consumption decision variable has been defined as EC_s^k wherein 'k' signifies the various sources of energy consumption in this model namely, trucks for transportation, compaction equipment, soil stabilization equipment, dozers and graders, scrapers, excavators, and street lighting (Peurifoy et al., 2018). 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 7 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, EC_1^1 means that for EC1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The water consumption decision variable has been defined as WC_s^k wherein 'k' signifies the various sources of water consumption in this model (predominantly in road median landscaping) namely, sprinkler system, water sprinkled by water trucks etc. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 2 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WC_1^1 means that for WC1 (sprinkler system), strategy I has been selected which signifies one of the alternatives of sprinkler system type.

The materials decision variable has been defined as Mat_s^k wherein 'k' signifies the major materials which have the highest share of the total cost namely, asphalt, concrete, and excavation and backfill. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 3 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, Mat_1^1 means that for Mat1 (trucks for transportation), strategy I has been selected which signifies one of the alternatives of truck transport.

The waste management decision variable has been defined as WM_s^k wherein 'k' signifies the various sources of waste management in this model namely, waste reduction, reuse/recycle on site, materials sent to recycling facilities, materials sent to manufacturer, composting, and materials sent to landfills. 's' signifies the selection of one strategy (among various alternatives of strategies) to address certain ENVISION credits and earn associated points. 'k' ranges from 1 to 6 and 's' ranges from 1 to n (n being the number of alternatives for a particular credit). For instance, WM_1^1 means that for WM1 (waste reduction), strategy I has been selected which signifies one of the alternatives for waste reduction.

3.5.2 Task 2: Definition of objective functions

The objective functions are developed to address the tradeoffs defined above for the **phase 2**. These siloed objective functions help achieve – (1) maximization of points associated with each of the ENVISION credits under social sustainability, (2) maximization of points associated with each of the ENVISION credits under environmental sustainability, (3) minimization of life cycle cost (LCC), and (4) minimization of the GHG emissions.

Social sustainability objective function

The social sustainability objective function attempts to maximize the number of points associated with social sustainability (quality of life and leadership categories) in the ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ SS(S) = \sum_{k=1}^{13} Pts\left(QOL_s^k\right) + \sum_{k=1}^{11} Pts\left(LD_s^k\right) + \sum_{k=1}^{7} Pts\left(EC_s^k\right) + \sum_{k=1}^{2} Pts\left(WC_s^k\right) + \sum_{k=1}^{3} Pts\left(Mat_s^k\right) + \sum_{k=1}^{6} Pts\left(WM_s^k\right) \quad (69)$$

In Equation (69), social sustainability is calculated as a function of strategies under the quality of life and leadership category of ENVISION which have unique number of points for each of the credits under those categories. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's social sustainability points. These points are added together to find the level of social sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 18.

As can be seen from Figure 18, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (40)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the nine main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (69). Thus, in this case, we have six dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with social sustainability need to be maximized.

Environmental sustainability objective function

The environmental sustainability objective function attempts to maximize the number of points associated with environmental sustainability (resource allocation, natural world, and climate categories) in the

ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ EnvS(S) = \sum_{k=1}^{13} Pts(RA_s^k) + \sum_{k=1}^{11} Pts(NW_s^k) + \sum_{k=1}^{3} Pts(CL_s^k) + \sum_{k=1}^{7} Pts(EC_s^k) + \sum_{k=1}^{2} Pts(WC_s^k) + \sum_{k=1}^{3} Pts(Mat_s^k) + \sum_{k=1}^{6} Pts(WM_s^k) \qquad (70)$$

In Equation (70), environmental sustainability is calculated as a function of strategies under the resource allocation, natural world, and the climate categories of ENVISION which have unique number of points for each of the credits under those categories. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's environmental sustainability points. These points are added together to find the level of environmental sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 19.

As can be seen from Figure 19, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (41)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the nine main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (70). Thus, in this case, we have seven dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with environmental sustainability need to be maximized.

Resilience objective function

The resilience objective function attempts to maximize the number of points associated with resilience category in the ENVISION rating system based on all the strategies in each of the decision variables as described in the previous section.

$$Max\ RL(S) = \sum_{k=1}^{6} Pts\left(CL_s^k\right) + \sum_{k=1}^{7} Pts\left(EC_s^k\right) + \sum_{k=1}^{2} Pts\left(WC_s^k\right) + \sum_{k=1}^{3} Pts\left(Mat_s^k\right) + \sum_{k=1}^{6} Pts\left(WM_s^k\right) \qquad (71)$$

In Equation (71), resilience is calculated as a function of strategies under each of the credits under the resilience category of ENVISION. Furthermore, the decision variables like energy consumption, water consumption, materials, and waste management contribute towards the ENVISION's resilience points. These points are added together to find the level of social sustainability. A graphical representation of conceptualization of the function of points to calculate the total points has been shown in Figure 28.

As shown in Figure 28, there are different number of sub-variables and strategies under the nine major decision variables (as defined in the objective function in Equation (71)), each decision variable can be visualized as a matrix of points achieved by strategies under each of the five main decision variables; the rows of this matrix correspond to the ENISION credits and the columns correspond to the strategies under each of the nine major decision variables. Therefore, we have multiple matrices which can be visualized as a representative of n^{th} dimension, where n corresponds to the variable as per the above objective function in Equation (59). Thus, in this case, we have five dimensions and the maximum points under each of the ENVISION credits need to be calculated and added together to get the total points; thereafter, these total points associated with resilience need to be maximized.

Life cycle cost objective function

The life cycle cost (LCC) objective function attempts to minimize the life cycle cost associated with the strategies adopted within the nine decision variables (Scheving, 2011; Sompura & Avetisyan, 2017).

$$Min\ LCC(S) = \chi_o + \left\{\sum_{n=1}^{LC/15} \frac{Y}{(1+i)^{15n}} + \sum_{n=1}^{LC/5} \frac{Z}{(1+i)^{5n}}\right\} - \frac{S}{(1+i)^N} \quad (72)$$

$$S = P - (Annual\ Depreciation \times Useful\ life) \qquad (73)$$

Here χ_o refers to the initial cost (or first cost) of the strategies as described in Equation (74). The computation inside curly brackets corresponds to the operations and maintenance phase. It consists of rehabilitation cost (variable Y) signifying the maintenance, and street lighting and water consumption costs (variable Z) signifying the operations. It has been determined that the rehabilitation of a road projects should be done every 15 years on an average and the maintenance activities are usually done every five years (Portland Bureau of Transportation, 2021). Therefore, the values for variable Y have been calculated and added together, after every 15 years throughout the life cycle; values for variable Z have been calculated and added together after every five years throughout the life cycle. Variable S determines the salvage value as defined in Equation (42).

$$\chi_o = \sum_{k=1}^{13} IC(QOL_s^k) + \sum_{k=1}^{11} IC(LD)_s^k + \sum_{k=1}^{13} IC(RA_s^k) + \sum_{k=1}^{13} IC(NW_s^k) + \sum_{k=1}^{3} IC(CL_s^k) + \sum_{k=1}^{6} IC(CR_s^k) + \sum_{k=1}^{7} IC(EC_s^k) + \sum_{k=1}^{2} IC(WC_s^k) + \sum_{k=1}^{3} IC(Mat_s^k) + \sum_{k=1}^{6} IC(WM_s^k) \quad (74)$$

Here IC represents the initial cost; IC(QOL) means initial cost as a function of quality-of-life strategies.

$$Y = \sum_{k=1}^{7} RC(EC_s^k) + \sum_{k=1}^{2} RC(WC_s^k) + \sum_{k=1}^{3} RC(Mat_s^k) \qquad (75)$$

RC represents the rehabilitation cost; RC(EC) means rehabilitation cost as a function of energy consumption strategies.

$$Z = \sum_{k=1}^{7} OC(EC_s^k) + \sum_{k=1}^{2} OC(WC_s^k) \quad (76)$$

OC signifies the operations cost; OC(EC) signifies the operating cost of street lighting throughout the life cycle of the project. OC(WC) means operating cost as a function of water consumption strategies.

To facilitate the calculation of the salvage value, the present value can be calculated as below.

$$PV = \sum_{k=1}^{13} PV(QOL_s^k) + \sum_{k=1}^{11} PV(LD_s^k) + \sum_{k=1}^{13} PV(RA_s^k) + \sum_{k=1}^{13} PV(NW_s^k) + \sum_{k=1}^{3} PV(CL_s^k) + \sum_{k=1}^{3} PV(CRL_s^k) + \sum_{k=1}^{7} PV(EC_s^k) + \sum_{k=1}^{2} PV(WC_s^k) + \sum_{k=1}^{3} PV(Mat_s^k) + \sum_{k=1}^{6} PV(WM_s^k) \quad (77)$$

Here PV represents the present value; PV(QOL) means present value as a function of quality-of-life strategies.

GHG emissions objective function

The GHG emissions objective function attempts to minimize the emissions due to adoption of strategies under each of the nine decision variables.

$$Min\ GHGE(S) = \sum_{k=1}^{13} E(RA_s^k) + \sum_{k=1}^{13} E(NW_s^k) + \sum_{k=1}^{3} E(CL_s^k) + \sum_{k=1}^{6} E(CL_s^k) + \sum_{k=1}^{7} E(EC_s^k) + \sum_{k=1}^{2} E(WC_s^k) + \sum_{k=1}^{3} E(Mat_s^k) + \sum_{k=1}^{6} E(WM_s^k) \quad (78)$$

The GHG emissions as a function of strategies need to be minimized and is expressed as the total emissions associated with the strategies under each of the associated decision variables.

Approach 1 – combining objectives

$$Max\ FitFunc = (W_1 \times SS) + (W_2 \times EnvS) + (W_3 \times Res) - (W_4 \times LCC) - (W_5 \times GHGE) \quad (79)$$

The above equation uses weighted aggregation of various objectives to maximize the total value. In Equation (79), W_1, W_2, W_3, W_4, and W_5 correspond to the weights wherein these values vary between 0 and 1. By varying the weights between 0 and 1, a pareto front can be obtained which represents a set of non-dominated solutions. The variation of the weights can be mathematically represented on a hyperplane as the weight vector will always have a cardinality less than that of the objectives vector (Messac, 2015). The model has been kept flexible to provide the option for the user to enter the weights which correspond to the variables' relative importance.

Approach 2 – separating objectives

This approach uses a multiobjective approach which has been described in 3.3.4 Task 4: Implementation of optimization model.

3.5.3 Task 3: Definition of model constraints

Several constraints have been defined in this model to mimic the real-world expectations and constraints – (1) GHG emission threshold constraint, (2) budget constraint, (3) level of sustainability, and (4) level of resilience.

Constraint 1 – GHG emissions

According to APTA SUDS-CC-RP (2009), the public transportation emissions are usually in a range of 0.12 to 1.2 lbs. of CO_2 per mile. Using this information, the GHG emissions threshold constraint for this model has been shown in Equation 80.

$$\frac{Total\ GHGE}{Total\ mileage} \leq 1.2\ lbs\ CO_2 \qquad (80)$$

Constraint 2 - Budget

The budget constraint will be defined by the user/owner entity, and it will serve as an upper limit for the total initial cost (first cost).

$$\sum_{n=1}^{9} \chi_o \leq Budget \qquad (81)$$

Constraint 3 – Level of sustainability

The minimum level of overall sustainability has been derived from the lowest certification level in the ENVISION rating system, which is the verified level, and is awarded when a project attains 20% of the total points. Since this phase is accounting for just the sustainability categories and credits, the total points under this phase are 874 points. The overall minimum level of sustainability can be defined by the following equation.

$$LOS \geq 175\, points \qquad (82)$$

Constraint 4 – Level of resilience

The minimum level of overall resilience has been derived from the lowest certification level in the ENVISION rating system, which is the verified level, and is awarded when a project attains 20% of the total points. Since this phase is accounting for just the sustainability categories and credits, the total points under this phase are 874 points. The overall minimum level of sustainability can be defined by the following equation.

$$LOS \geq 25\, points \qquad (83)$$

3.5.4 Task 4: Implementation of optimization model

In this optimization model, the objective functions are applied to dataset and feasible solutions are found based on a set of constraints. The model starts with definition of the input dataset(s) for each one of the decision variables as described above. Thereafter, the model uses Linear Programming as the base algorithm and applies the objective functions defined above to maximize sustainability and resilience and minimize the greenhouse gas (GHG) emissions and life cycle cost (LCC). Lastly, the model finds the optimal solution (or set of optimal solutions) while exploring the computational time to reach the optimal. A graphical representation of the implementation of the optimization model has been shown in Figure 36.

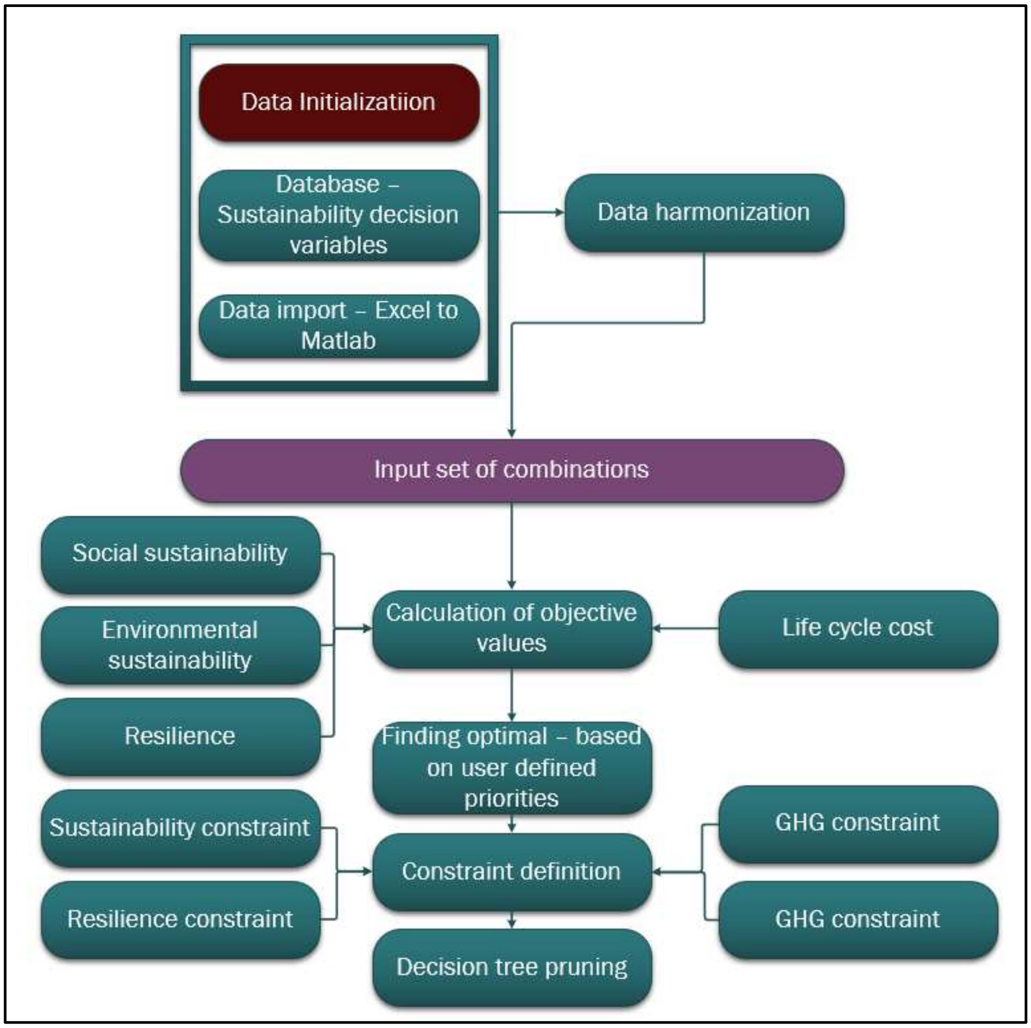

Figure 34: Flow of higher-level sustainability and resilience optimization process

As shown in Figure 34, the search for an optimal solution starts with data initialization through an excel-based dataset. It consists of details pertaining to each of the major objectives such as sustainability, resilience, life cycle cost (LCC), and greenhouse gas emissions (GHG) for several strategies under each of the nine decision variables. This dataset is subject to frequent addition by users to ensure the comprehensiveness and adaptability of the dataset to various regions depending on the location of a project. Naming convention for the column headings and variable names have been kept consistent for easy understanding of any user or programmer. The excel-based dataset for all decision variables is imported into MATLAB which completes the data initialization process.

Data harmonization consists of appropriately categorizing the imported data into each of the sub-decision variables. For instance, the data for quality-of-life category under ENVISION that contributes to social sustainability contains all relevant strategies for each of the associated credits. To ensure that only one strategy is selected for every credit, this data needs to be categorized as per the resilience credits.

The constraints are defined in the MATLAB and are used to prune the search space. Since the level of resilience contain a minimum points constraint for resilience, pruning will help reduce the search space when a large data inventory is being input. This can significantly reduce the computational time to find the optimal solution.

One strategy from each sub-decision variable is chosen that helps create a set of combinations. Each of these combinations represent potential solutions to our optimization problem. These combination sets are pruned further by eliminating the combinations which have a total cost greater than the user-specified budget. Though linear programming would have been the best algorithm for solving our optimization problem as both the objective function and all associated constraints are linear, however, the decision variables in our research only take discrete values. Therefore, linear programming cannot be used in this case as it takes discrete values for decision variables (Martinich, 2008; University of Kentucky, 2015). In the realm of discrete optimization, the problems are further broken down into five major categories (Messac, 2015):

1. Pure integer programming problems: this problem type is applied when the decision variables can only take integer values.
2. Mixed-integer programming problems: this problem type is applied when the decision variables can take a mixture of integer and continuous values.
3. Discrete non-integer problems: this problem type is applicable to scenarios where we have a discrete input dataset.
4. Binary programming problems: this problem type is applicable to scenarios where decision variables can only take values zero or one.

5. Combinatorial optimization problems: this problem type is applicable to scenarios where "the feasible solutions are defined by a combinatorial set resulting from the given feasible discrete values" of the decision variables.

The decision variables in this research are discrete and potential solutions would represent a combination of different feasible values, a combinatorial optimization is suitable for solving the optimization problem proposed in this phase. Furthermore, because the variables in this research are discrete and they represent an unordered state space which validates the usage of combinatorial optimization using heuristic methods (Arsham, 2015; Messac, 2015).

As discussed in 3.4.2 Task 2: Development of objective functions, various objectives in this optimization problem can either be combined or kept separate. Weighted sum model, linear programming with relaxation approach, and branch and bound are a few classical optimization techniques which can be applicable to the scenario where objectives are combined. The weighted sum model is one of the easiest techniques to apply and it uses the exhaustive search to search for the optimal in the state space (space that graphically defines the position of optimal solution(s)). Since this technique uses an exhaustive search, its application becomes tedious due to the size of the model's dataset being exponential (Messac, 2015). In the linear programming with a relaxation approach, the problem is assumed as continuous, and the optimal solution is rounded off to the nearest feasible solution. However, in our optimization model, the set of potential combinations would need to be calculated to gauge the value in the discrete dataset that has the least distance to the assessed optimal. Therefore, it diminishes the use of this relaxation technique due to the need of calculation of objective values through an exhaustive approach. The branch and bound technique use the relaxation approach as the underlying algorithm, and therefore it has not been used for optimization for the same reason. In addition to the discussed limitations, these techniques will result in one optimal solution at the end of each simulation.

Usage of evolutionary approaches like genetic algorithm, simulated annealing, particle swarm optimization, and ant colony optimization among many others is recommended for the combinatorial optimization problem portrayed in this phase. These techniques explore numerous non-dominated solutions in just one simulation, thus reducing the computing time (Savic, 2002; Srinivas & Deb, 1994). The most widely applicable and robust evolutionary technique is the genetic algorithm (GA), and therefore, it has been used to find a set of optimal solutions for the resilience optimization model (Abdallah & El-Rayes, 2016; Brunelli et al., 2016; Hashim et al., 2017; Rasi & Sohanian, 2020; Savic, 2002; Srinivas & Deb, 1994). This research uses the non-dominated sorting genetic algorithm (NSGA-II) to find the pareto set of optimal solutions for the various objectives detailed in **Task 2**. In this algorithm, first an initial population is generated which consists of a fixed number of chromosomes. These chromosomes denote the potential solutions (or combination of strategies) to achieve the different objectives. First the mutation and crossover operations of the genetic algorithm (GA) are applied to the initial population (also known as the parent population, Pt) and several children are generated to form the child population (Qt). These two GA operations have been described below.

A summary of the NSGA-II methodology detailed above, has been represented in Figure 35.

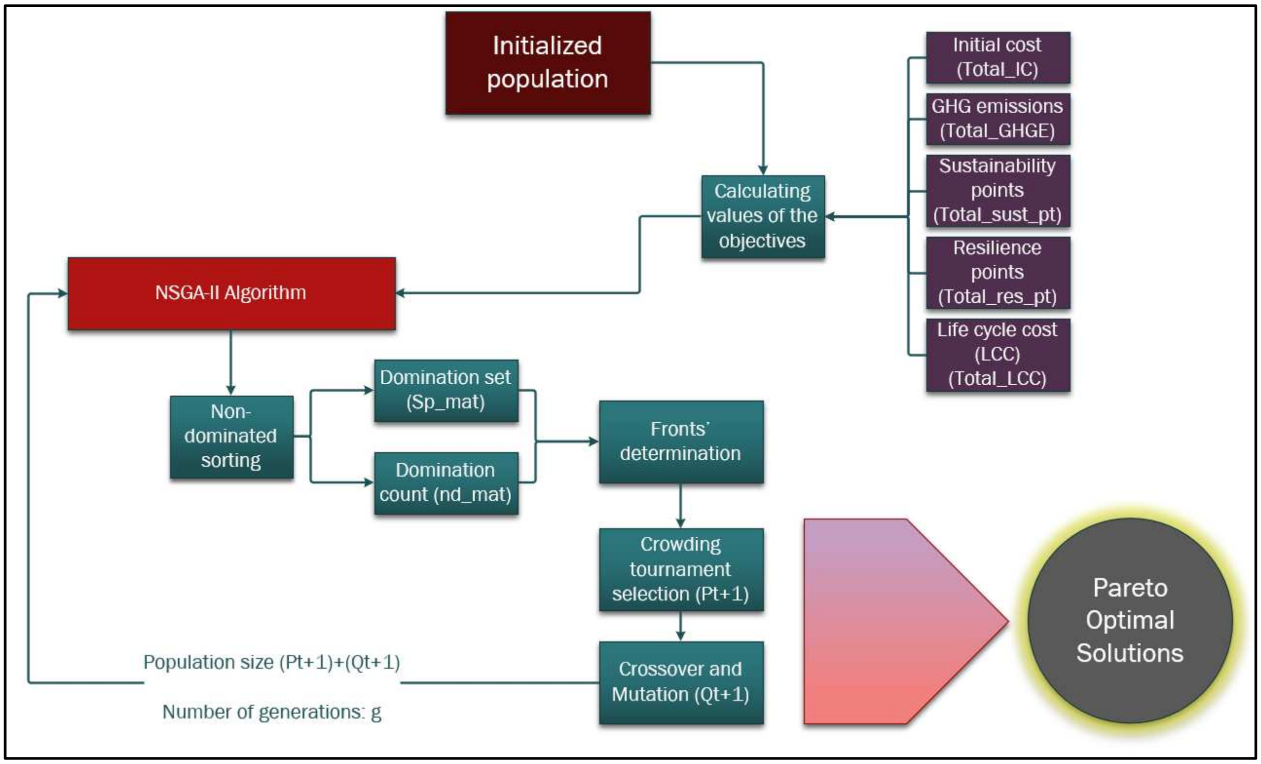

Figure 35: NSGA-II methodology (sustainability and resilience)

The NSGA-II methodology remains same as defined in detail in 3.3.4 Task 4: Implementation of optimization model, with the only difference of the various objectives being input into the optimization model.

3.5.5Task 5: Model application – case study

The case study used in this research is a highway project in Colorado which was constructed in 2020 and managed by Colorado Department of Transportation (CDOT). As there are no ENVISION certified roads and highway projects in Colorado, the CDOT project mentioned above was undertaken for the purpose of case study and several sustainable and resilient initiatives were introduced for the ENVISION rating system to be applicable. Thereafter, the integrated optimization model was used to select the strategies which can help to achieve the highest level of sustainability and resilience while ensuring that the life cycle cost, and greenhouse gas (GHG) emissions are minimized.

4 Results

4.1 Phase 1 results

There is a wide variety of stakeholders involved in the construction and maintenance of transportation sector projects have different perceptions and understanding of the sustainability and resilience. Therefore, it makes the adoption of sustainability and resilience through the planning and design phases an arduous task. This is one of the reasons why sustainability and resilience have had different meanings among the various stakeholders.

The terms "sustainability" and "resilience" have been used interchangeably in a siloed or loose manner across different disciplines. Spacey (2016) compared sustainability and resilience and found that they are using similar techniques, yet further stated that "resilience associated with cities whereas sustainability is a much broader perspective". Another article focusing on California's water resources expressed the debate among policymakers about adopting either sustainability or resilience (Water Education Foundation, 2016). This lack of understanding of the differences and integrative nature of these concepts can impede the adoption of both sustainability and resilience. Considering that sustainable cities cannot exist without them being resilient, and resilient cities cannot be created without sustainability as being one of the prime objectives, having a focus on one or the other is detrimental to the holistic development of societies. Cederoth and Brown (2021) showed resilience should be looked at from the lens of sustainability. This means analyzing the sustainable aspects of being resilient. Though there are benefits to doing this, it does overshadow the importance of resilience, considering that the resilience of cities requires different planning and management than the sustainability of cities. Elmqvist (2017) argued the need for having a better set of definitions of sustainable and resilient development for systematic adoption of both.

4.1.1 Synthesizing the quantification literature

After understanding the various methods to quantify sustainability and resilience, it was observed that rating systems provide a great metric for sustainability assessment, however, they lack a detailed quantification of resilience (and its dimensions). Analyzing the formulae used in the quantification of resilience and its dimensions helped to create a standardized list of variables that need to be considered for the quantification.

Table 11: Summary of variables used to quantify robustness

Authors	**Robustness Variables**				
	Functionality/Performance/Quality	**Probability**	**Conditional Probability**	**Failure rate**	
(Walsh et al., 2013)	X	X			
(Faber et al., 2006)		X	X		
(Bruneau & Reinhorn, 2007)	X				
(Cimellaro et al., 2010)	X				
(Ayyub, 2014)	X			X	
Authors	**Resourcefulness Variables**				
	Redundancy	**Human element/skills**	**Resource mobilization capacity**	**Political and economic scenario**	**Infra components prioritization**

(Fisher et al., 2010)	X	X			
(Cimellaro et al., 2010)	X				
(Didier et al., 2018)			X		
(Zona, 2019; Zona et al., 2020)		X		X	
(Balakrishnan & Zhang, 2020)					X

Authors	**Recovery Variables**				
	System performance/ state	**Failure**	**Resource availability**	**Rapidity**	**Recovery time**
(Hashimoto et al., 1982)	X	X			
(Attoh-Okine et al., 2009)	X				
(Bruneau & Reinhorn, 2007)			X		
(Ouyang et al., 2012)			X		
(Cimellaro et al., 2010)				X	

(Ayyub, 2014)	X				
(Francis & Bekera, 2014)					X

4.1.1.1 Variable coverage and coherence – robustness

Most researchers used a similar quantification metric for system robustness. However, the method of quantifying the system was slightly different. While some researchers used performance as a function of time as the variable (Ayyub, 2014; Bruneau & Reinhorn, 2007; Cimellaro et al., 2010; Walsh et al., 2013), other researchers used risk to quantify robustness of the system (Faber et al., 2006). Table 11 summarizes the variables used in to quantify robustness.

This research proposes adopting the variables such as functionality/performance/quality and conditional probability for the most accurate and easier robustness quantification. This is because the performance variable can capture the pre- and post-disaster levels which are of prime importance robustness quantification. Furthermore, the conditional probability is needed to identify the probability of failure when a specific disaster occurrence is known. Failure rate has not been suggested explicitly because it can be calculated based on the other three variables.

4.1.1.2 Variable coverage and coherence – resourcefulness

Resourcefulness has been difficult to quantify due to the presence of a human element (Cimellaro et al., 2010). In spite of a challenging quantification metric, a few researchers did propose variables that can be used to quantify resourcefulness, however, there does not seem to be a consensus or overlap in their approaches. Table 11 summarizes the variables used (or can be used) to quantify resourcefulness.

This research proposes that a resourcefulness index approach should we followed similar to the one adopted by Zona et al. (2020), however, inclusion of all the variables mentioned in Table 11 **Error! Reference source not found.**is recommended. This is because all the variables holistically address how a community responds to a disaster. Contrary to a majority of research efforts, some researchers defined and quantified resourcefulness as a function of recovery (Sharma & Chen, 2020). It should be noted that in this research study, recovery is another dimension and should be kept separate from resourcefulness.

4.1.1.3 Variable coverage and coherence – recovery

Though various approaches have been followed by researchers to quantify recovery, it should be noted that the underlying theme is consistent among all quantifications. Table 11 summarizes the variables used to quantify system recovery.

After reviewing the various quantification approaches, this research proposes adopting system performance, resource availability, and rapidity as the variables to quantify system recovery. System performance is necessary to quantify the post-disaster level and the post-recovery levels; resource availability is one of the biggest constraints to achieving the recovery; and rapidity combines the system performance and the recovery time into one equation. Failure and recovery time have not been suggested to be explicitly adopted because they can be subsumed under the quantification of other variables presented in Table 11.

4.1.1.4 Variable coverage and coherence – adaptability

Adaptability is one of the most vaguely defined dimensions of resilience and it is the only dimension that lacks a quantification specific to infrastructure adaptability. The quantification proposed by Perez-Palacin et al. (2014) has been the only one that comes close to addressing an infrastructure system, however it should be noted that their quantification pertains towards electronics systems. Though it might seem like a qualitative dimension, adaptability can certainly be quantified by leveraging concepts from the electronics and communications sector.

4.1.2 Interconnection of sustainability and resilience

Buildings and infrastructure components often focus on very specific (and easily achievable) aspects of either sustainability or resilience. A common misconception among these stakeholders is that the adoption of both sustainability and resilience is expensive; this perception exists within several divisions of the US government which own and manage infrastructure systems (roads, highways, dams, etc.). Kumar and Mehany (2020) tried to address this perception wherein a decision-making framework for the stakeholders facilitated the adoption of a greater level of sustainability within a given budget among other constraints. One of the research studies by Redman (2014) validates the thought about sustainability and resilience being different concepts but intertwined concepts. This research agrees with the discussion about sustainability adoption needing resilience adoption in the planning phase and vice versa.

Boarnet (1997) implied that sustainability planning does not always require a tradeoff between economic, social, and environmental objectives, but rather finding strategies that help achieve all these objectives over the long term by increasing transportation system efficiency. Tupper et al. (2012) suggested that these strategies can compete in cost aspects yet careful selection can be made using optimization methods Replogie (1991) suggested a long-term cost assessment of various sustainable strategies to optimize the impacts with respect to the total life cycle costs. Similarly, Schraven and Hartmann (2010) found a tradeoff between public interests (e.g. affordability, sustainability, safety, accessibility, and robustness) and financial investments and suggested efficient decision making by involving the community and including the life cycle assessment of various options. In the meantime, the implementation of resilient strategies need to be sustainable to reduce the environmental, social, and economic impacts, therefore suggesting that there is a tradeoff between resilience and sustainability (Salas & Yepes, 2020).

Through three case studies, Chelleri et al. (2015) developed and implemented a resilience framework. They emphasized that this resilience framework should always be associated with sustainability.

Bocchini et al. (2014) imposed that sustainability and resilience were complementary and recognized the existence of tradeoff between the two theories. Furthermore, Bocchini et al. (2014) combined resilience and sustainability while accounting for the hazardous events as in Equation (38). Lastly, these authors encouraged future research to incorporate probabilistic scenarios when optimizing resilience and sustainability.

Salas and Yepes (2020) developed an optimization model to enhance the sustainability and resilience through multi-level infrastructure planning. They identified a lack of research in implementing resilience strategies that are also sustainable. A multi-objective model helped in identification of key planning alternatives and their impact on vulnerable entities and the results showed a strong correlation between planning alternatives and risks associated with such a combined implementation of resilience and sustainability. Recently, a new framework was developed to address the tradeoff between resilience, sustainability, and the level of service (also an indicator of system performance) and applied it to seven different cities. An optimization model was used to determine the pareto front that indicated the maximization of sustainability while minimizing the associated risk and reducing the global footprint of each of the cities (Krueger et al., 2020). Valenzuela-Venegas et al. (2020) introduced an optimization model to solve five objectives – individual considerations of economic sustainability, environmental sustainability (failed to account for social sustainability), resilience; tradeoff between economic and environmental sustainability; and simultaneous consideration of economic sustainability, environmental sustainability, and resilience. They glorified the importance of solving single objectives as it provided the best alternative for each objective. Multiple objectives on the other hand establish the best alternative that maximizes the resilience and sustainability.

4.2 Phase 2 results

The sustainability optimization model used the NSGA-II algorithm wherein an initial population of 10 members were initialized and the algorithm was run for 5,000 generations. This model generated a pareto front after application of the NSGA-II methodology as defined in section 3.3.4 Task 4: Implementation of optimization model. This pareto front represents the set of potential solutions which adhere to the model constraints and achieve the various objectives (maximize sustainability, minimize life cycle cost, and greenhouse gas emissions). The pareto front has been shown in Figure 36, Figure 37, Figure 38.

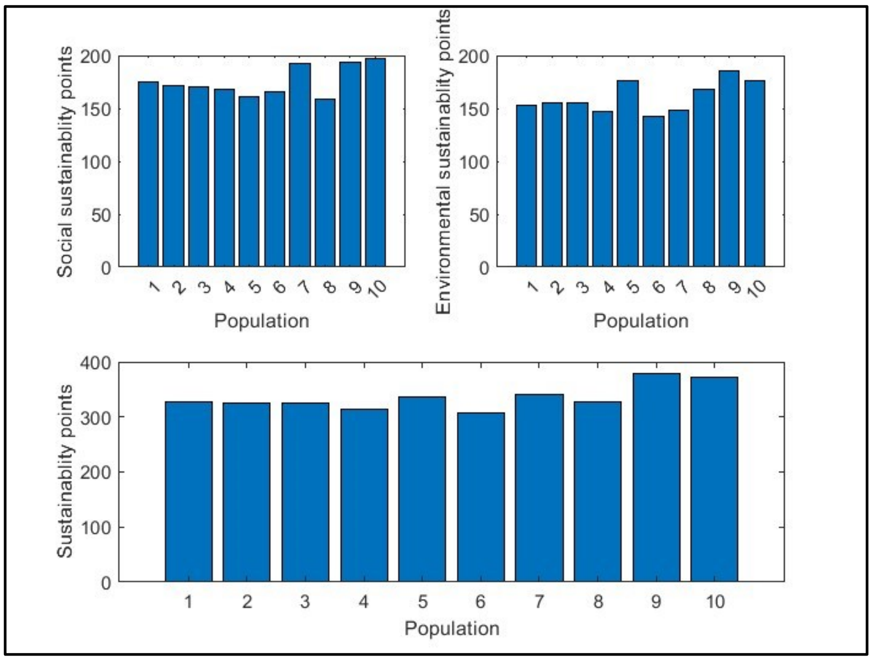

Figure 36: Sustainability of the pareto solution

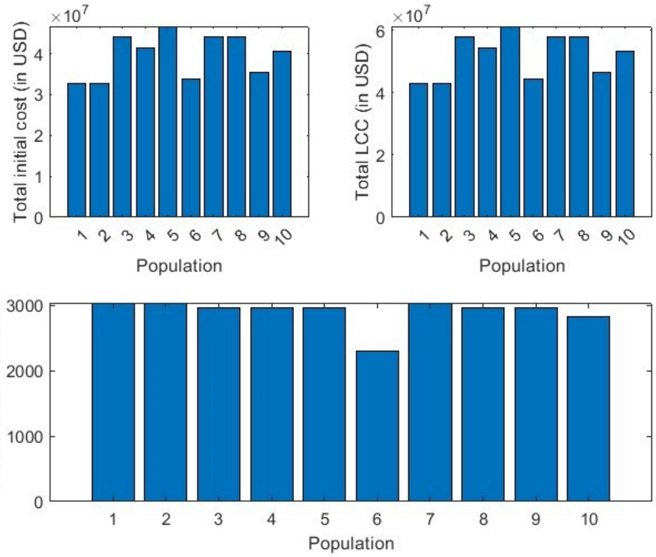

Figure 37: Objectives' values for the pareto solution (sustainability)

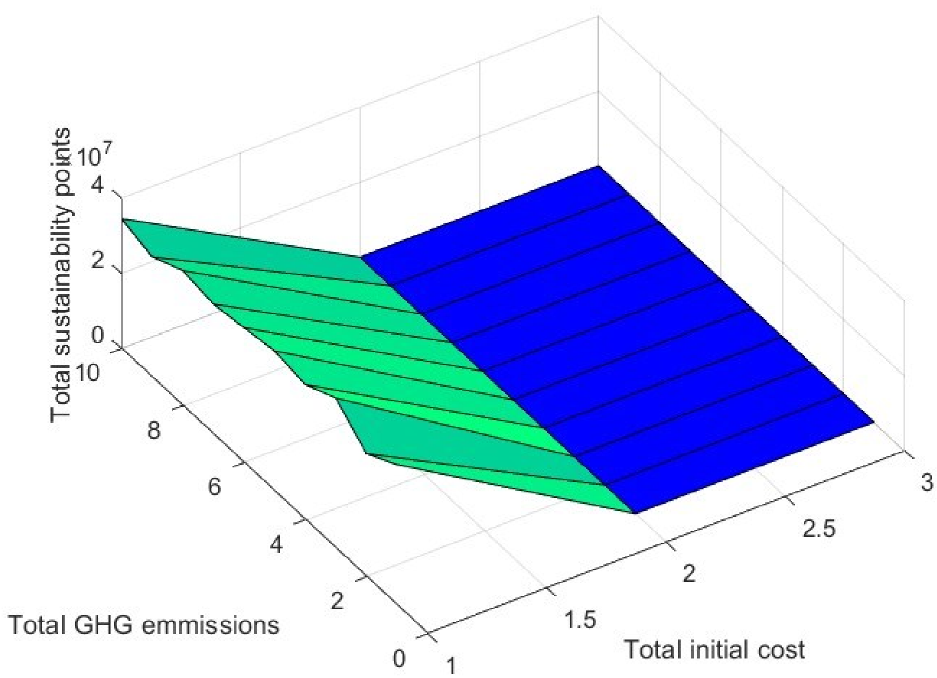

Figure 38: Pareto front representation (sustainability)

The constraints were applied, and decision tree pruning was implemented to determine the acceptable set of pareto solutions, which can be recommended to the decision makers. This recommended list has been shown in Figure 39.

Parent_chrom

10x57 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	2	2	2	1	2	2	1	1	1	1	1	2	2	1
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
3	2	2	2	1	2	2	2	2	2	2	2	2	2	1
4	2	2	2	1	2	2	1	2	2	2	2	2	2	1
5	2	2	2	2	2	2	1	2	2	1	2	2	2	2
6	2	2	2	2	2	2	2	2	2	2	1	2	2	2
7	2	2	2	2	2	2	2	2	2	2	2	2	2	2
8	2	2	2	2	2	2	1	2	2	1	2	2	2	2
9	2	2	2	2	2	2	2	2	2	2	2	2	2	2
10	2	2	2	2	2	2	2	2	2	2	2	2	2	2

Figure 39: Excerpt of the pareto front (sustainability)

The pareto shown here is an excerpt and just shows 14 columns, however, the full pareto has 57 columns. Each row defines a combination set that can be selected by the stakeholders. For example, the first row defines the first recommended solution. Here strategy 2 is selected for the QL1.1 credit, strategy 2 is selected for the QL1.2 credit, strategy 2 is selected for the QL1.3 credit, strategy 1 is selected for the QL1.4 credit, and so on.

4.3 Phase 3 results

The resilience optimization model used the NSGA-II algorithm wherein an initial population of 10 members were initialized and the algorithm was run for 5,000 generations. This model generated a pareto front after application of the NSGA-II methodology as defined in section 3.4.4 Task 4: Implementation of optimization model. This pareto front represents the set of potential solutions which adhere to the model constraints and achieve the various objectives (maximize resilience, minimize life cycle cost, and greenhouse gas emissions).

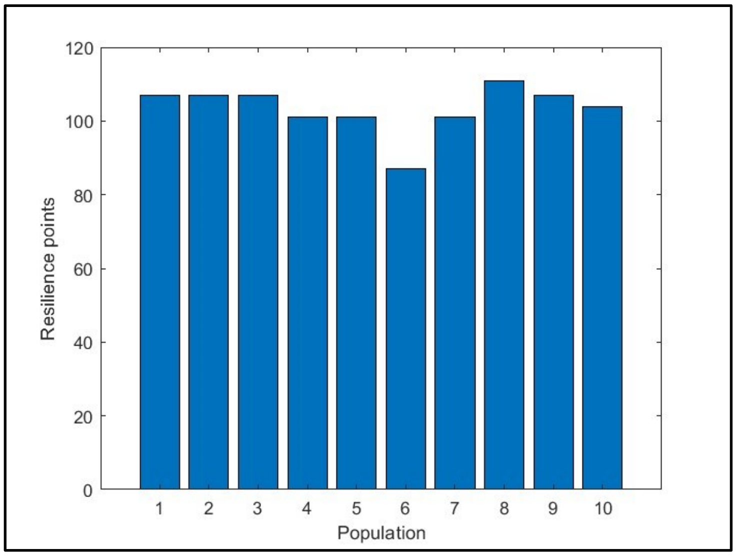

Figure 40: Resilience of the pareto solution

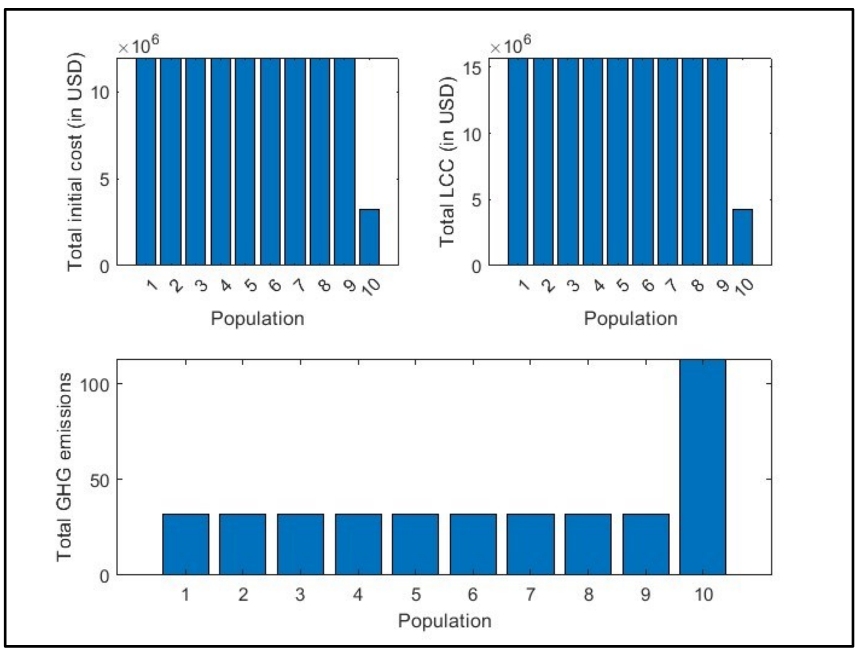

Figure 41: Objectives' of the pareto solution (resilience)

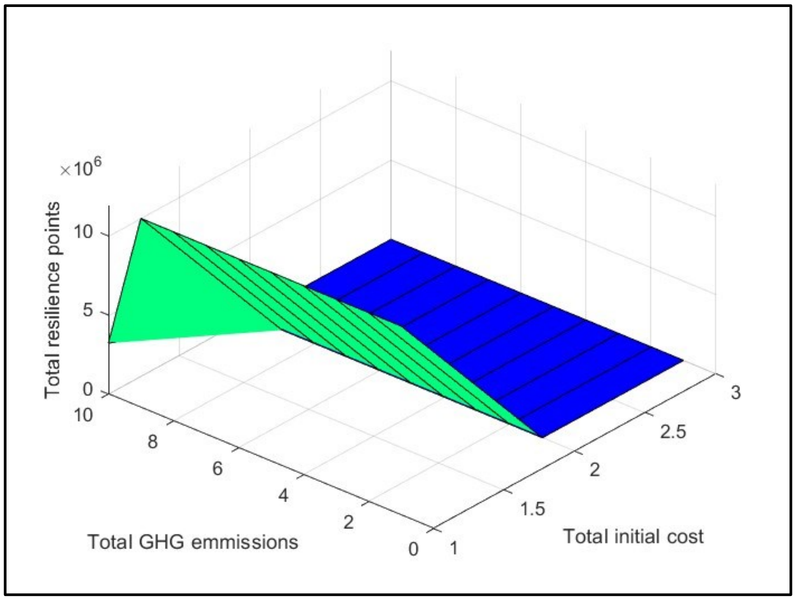

Figure 42: Pareto front representation (resilience)

Furthermore, the ENVISION credits for resilience can be modified to make the intent of credits more detailed and the quantification more accurate. Several infrastructure rating systems were explored in the literature and the coverage of resilience was explored. Using the different infrastructure systems and the research on quantification of the four dimensions of resilience helped to develop the indicators within those dimensions.

Table 12: Proposed credits for Robustness

Code	Name	Intent
R1.1	Disaster risk and reliability assessment	To identify potential hazards and analyze the potential impacts cumulatively from all hazard types. OR To assess the infrastructure's ability to functionally operate under disastrous conditions

		(and general operating conditions) for a designated period of time.
R1.2	Disruption preparedness	To increase and heighten the effectiveness of managing disruption emergencies and mitigate the harm to communities and stakeholders affected by the disruption.
R1.3	Functional capacity	To increase the functional capacity of the project by identifying issues that have varying severity levels
R1.4	Effective commissioning	To assess the reliability and efficiency of an infrastructure project and compare it to the planned functional levels

Table 12 describes the different credits which can be used to quantify robustness of a system. Determining the risk and reliability of a system is pivotal in defining the robustness. Disruption preparedness accounts for the social aspect of robustness and ensures that a community is prepared for any disaster scenario.

Table 13: Proposed credits for resourcefulness

Code	**Name**	**Intent**
R2.1	Emergency response planning	To facilitate the preparation of an emergency response plan and procedure, so that the local authorities (and the project) are prepared to effectively respond to a disaster, thus

		minimizing the consequences (both human injury/death and monetary impacts)
R2.2	Redundancy and alternative measures	To assess the project's capacity to offer alternatives which are capable of fulfilling the functional requirements during disruptions
R2.3	Disaster response technology	To promote the presence of technology to enhance the coordination of emergency services, monitoring, and provision of regular updates regarding the status of disaster
R2.4	Emergency resource provision	To assess the project's ability to facilitate resource availability and their accessibility during a disaster
R2.5	Community collaboration	To encourage the project team to coordinate with the community and engage them in creating a plan to ease the response process

In the above table, resourcefulness is represented by the different aspect of disaster response during the time disaster scenario is in effect. It shows that technology, resources, system redundancy, and community are important to withstand a disaster.

Table 14: Proposed credits for recovery

Code	**Name**	**Intent**
R3.1	Post-disaster condition assessment	To assess the condition/functionality of the infrastructure project post-disaster

R3.2	Rapidity	To assess the speed of the infrastructure to return to an acceptable functionality after disruptive events while minimizing TBL impacts
R3.3	Optimizing the pre-event functionality	To assess the tradeoff between minimizing the duration of functionality restoration and maximizing resource provision
R3.4	Coordination and recovery time	To assess the inter-agency and external coordination efforts to reduce restoration duration while implementing the pre-defined emergency response plan
R3.5	Recovery planning	To detail the recovery plan which will serve as the guidance for the project and the local community to recover from a disaster

Recovery is one of the most crucial aspects of resilience and it requires both quantitative and qualitative aspects to minimize the recovery duration. Determining different paths for recovery and optimizing the best path is very important. It is essential to get the local community on-board and ensure that their buy-in is received to follow a specific recovery path.

Table 15: Proposed credits for adaptability

Code	**Name**	**Intent**
R4.1	Lessons learned	To have a protocol in place for continuous improvement (document, study, analyze, and update) through observations post-disasters

R4.2	Damage assessment technology	To soundly monitor the identified risk(s) and continually update technology through a comprehensive improvement program
R4.3	Future functional capacity	To plan and develop system expandability and increased functional capacity, according to the various observed and anticipated changes (e.g., climate change, potential natural disasters, etc.)
R4.4	Using alternative project delivery methods	To identify the potential of using more collaborative delivery methods such as DB, IPD to improve the planning, design, construction, and OM phases
R4.5	Re-evaluation of planning procedures	To understand the shortcomings of the existing plans and making necessary modifications to ensure that the project and the local community will be able to withstand future disasters
R4.6	Procedure for new tools and technologies introduction	To analyze various tools and technologies that could assist in similar future disaster events

Adaptability is an essential part of resilience which leverages the lessons learned to prepare for the future disasters. Using technology and the re-evaluation and modification of the disaster planning procedures, helps to maximize adaptability of a system.

4.4 Phase 4 results

The integrated sustainability and resilience optimization model used the NSGA-II algorithm wherein an initial population of 10 members were initialized and the algorithm was run for 5,000 generations. This model generated a pareto front after application of the NSGA-II methodology as defined in section 3.5.4 Task 4: Implementation of optimization model. This pareto front represents the set of potential solutions which adhere to the model constraints and achieve the various objectives (maximize sustainability, maximize resilience, minimize life cycle cost, and greenhouse gas emissions).

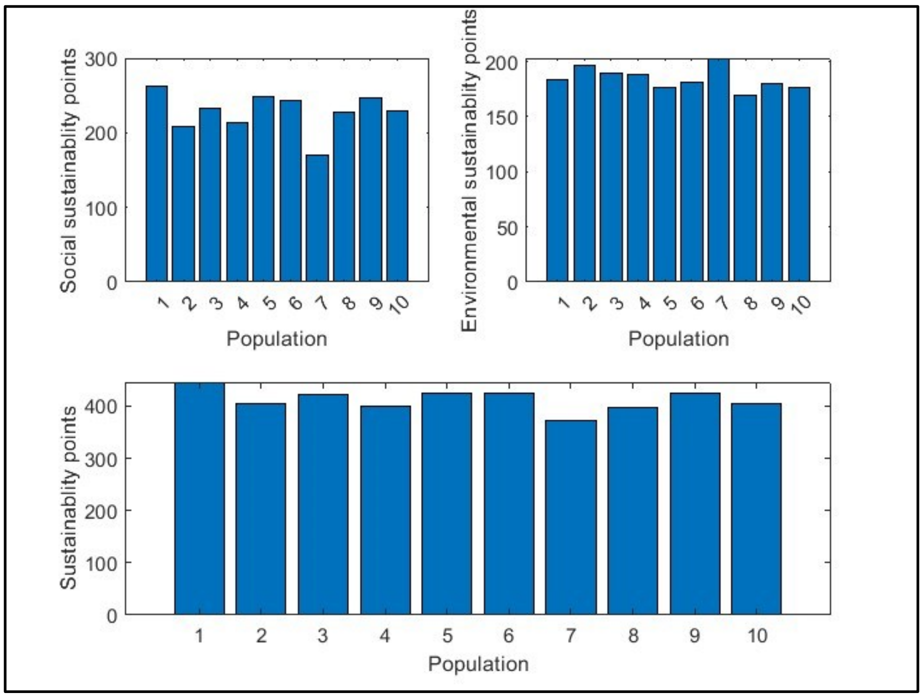

Figure 43: Sustainability of the pareto front (integrated)

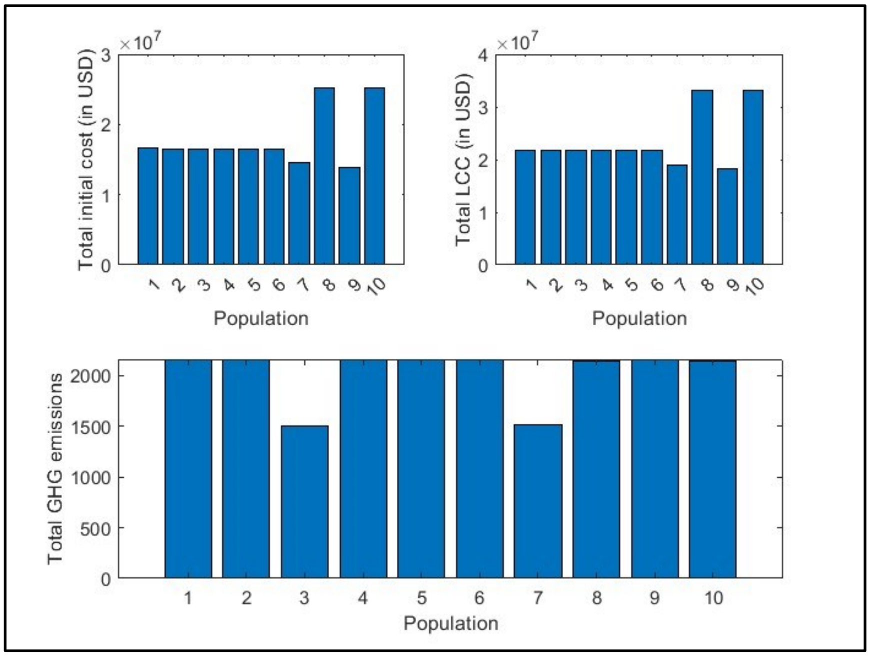

Figure 44: Objectives' of the pareto front (integrated)

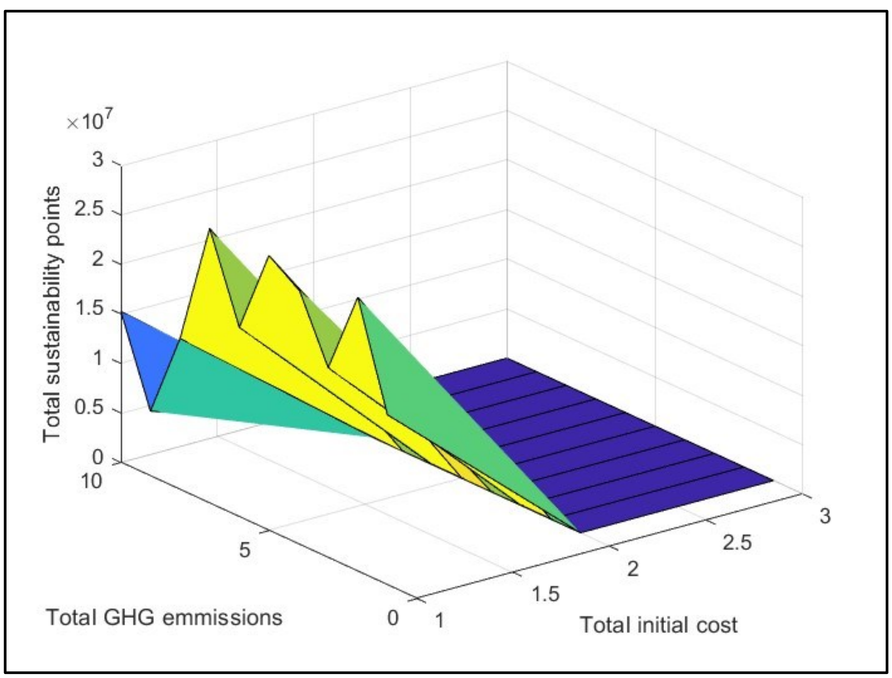

Figure 45: Pareto front (sustainability - integrated)

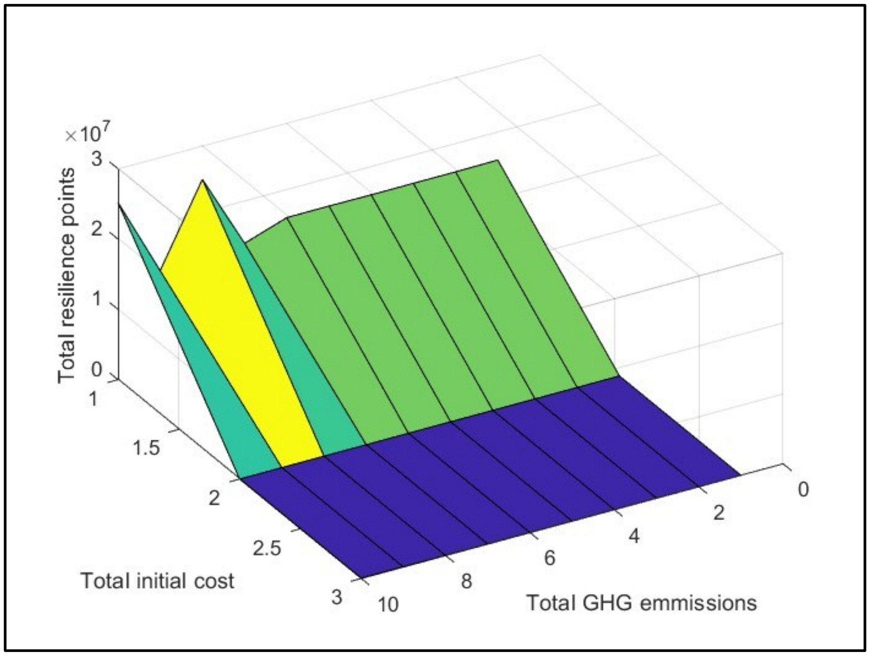

Figure 46: Pareto front (resilience – integrated)

The constraints were applied, and decision tree pruning was implemented to determine the acceptable set of pareto solutions, which can be recommended to the decision makers. This recommended list has been shown in Figure 47.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	5	5	3	3	4	3	4	1	3	4	1	1	2	3
2	3	5	3	5	3	2	4	1	3	4	4	2	3	1
3	5	2	3	3	4	3	4	1	4	1	1	2	3	1
4	5	5	3	3	4	1	4	1	1	4	1	1	2	2
5	5	5	3	3	4	3	4	1	3	1	1	1	3	1
6	3	2	3	3	3	3	4	1	4	4	4	2	3	3
7	3	5	1	3	3	3	4	1	3	1	4	2	3	3
8	5	5	3	3	3	3	4	1	3	3	1	2	3	1
9	5	5	3	3	3	3	4	1	3	3	1	1	2	3
10	5	5	3	3	3	3	4	1	3	3	1	2	3	1

Figure 47: Excerpt of the pareto front (integrated)

The pareto shown here is an excerpt and just shows 14 columns, however, the full pareto has 63 columns. Each row defines a combination set that can be selected by the stakeholders. For example, the first row defines the first recommended solution. Here strategy 5 is selected for the QL1.1 credit, strategy 5 is selected for the QL1.2 credit, strategy 3 is selected for the QL1.3 credit, strategy 3 is selected for the QL1.4 credit, and so on.

The model runs through several thousands of generations and a decreasing trend for the cost can be seen as shown in Figure 48. It is important to note that though the general trend is decreasing, we can see cost spikes and rare increases due to the randomness in the selection of initial population or the randomness in mutation and crossover operations.

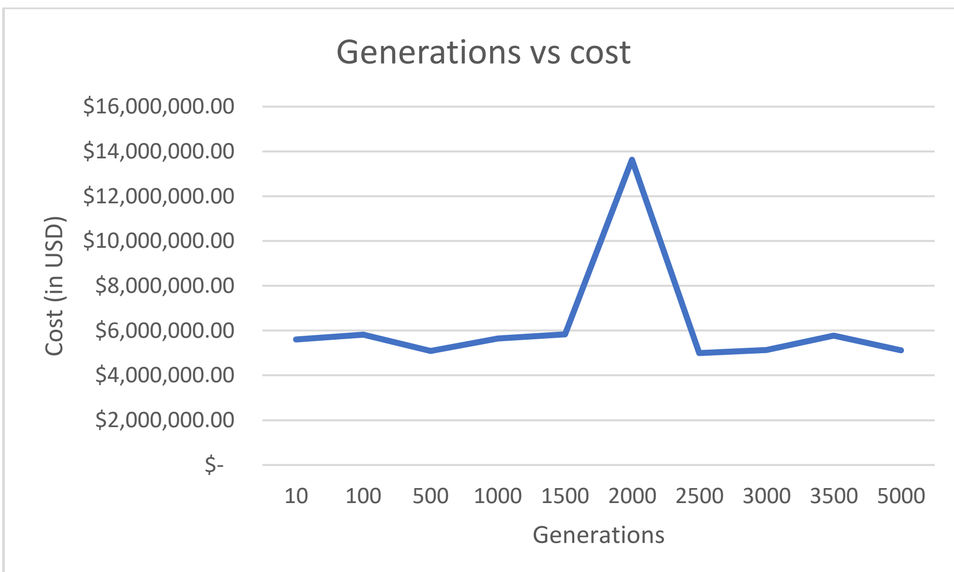

Figure 48: Analysis of number of generations vs cost

The above results show the success of the novel optimization model for sustainability and resilience. It also shows the fact that the most sustainable and resilient options aren't always the cheapest, and we need to explore a life cycle perspective when making decisions about the adoption of various strategies in the planning, design, and construction phases which impact the operations and maintenance phase.

5 Discussion and conclusion

5.1 Summary

This novel research proposed a multi-objective optimization model for sustainability and resilience improvement for transportation projects. This research was conducted in four phases where the first phase comprehensively explored the topics of sustainability and resilience and their associated quantification. Several rating systems were explored for the quantification of sustainability and resilience and ENVISION was chosen as the system for this research study. Inferring the existing studies from this phase, it was determined that there is a strong connection between sustainability and resilience and each aspect needs to be focused on individually and together. The next phases of this research use the MATLAB platform to code the NSGA-II evolutionary algorithm and search for a pareto optimal front. The second phase of this research focused on maximizing sustainability while minimizing cost. Using the ENVISION rating system as the guideline, several strategies were determined and the associated first cost and the life cycle cost (LCC) was calculated. The associated emissions were also calculated which helped to maximize sustainability and minimize the GHG emissions while simultaneously minimizing the LCC. The third phase of this research focused on maximizing resilience while minimizing cost. Using the ENVISION rating system as the guideline, several strategies were determined and the associated first cost and the life cycle cost (LCC) was calculated. The associated emissions were also calculated which helped to maximize resilience and minimize the GHG emissions while simultaneously minimizing the LCC. Furthermore, due to ENVISION's resilience credits being general, several credits under each of the dimensions of resilience (robustness, resourcefulness, recovery, adaptability) were suggested. In the last phase of this research, the main objectives represented in sustainability and resilience were maximized while reducing GHG emissions and LCC.

5.2 Research contribution and significance

The results show how a higher level of sustainability and resilience (represented by the number of ENVISION points) can be achieved within budget and also have low greenhouse gas emissions (GHG emissions). A unique method was developed to calculate the number of points associated with sustainability and resilience. A multi-dimensional matrix was created that consisted of 2D matrix from each of the different credits. This ensured that the points gained from different strategies for the same credit are counted only once. This was a novel approach formulated to calculate the number of sustainability and resilience points when there are numerous dependencies present between the decision variables in the optimization model.

The data harmonization process culminated in the creation of a database format that can be used for future studies to enter different strategies to achieve each credit, giving different levels of achievements. The format of this database was created in such a way that it will be easier for stakeholders to input data about the strategies, their associated cost and emissions, and the number of ENVISION points they could help to achieve. A database such as this could promote an open-access thinking among the different Departments of Transportations (DOTs) and motivate them to share information about strategies which could enhance the sustainability and resilience of transportation projects.

The results of this optimization model can assist the stakeholders with decision making with respect to sustainability and resilience. The models created for phases 2, 3, and 4 can facilitate a quicker decision-making process in the design phase and promote thinking from a life cycle perspective instead of focusing only on the first cost.

Sustainability optimization model (phase 2) can drive several design discussions to lower the environmental impact of transportation projects, promote a better quality of life not just for humans, but also wildlife, birds, and aquatic life, and improve the financial performance of the project. It is also important to note that the sustainability optimization model ensures that achieving one of the goals. For example, this is very beneficial by establishing minimum standards that can have drastic effects otherwise.

let's say promoting better quality of life) does not compromise achieving another goal (let's say financial performance).

Resilience optimization model (phase 3) can drive the discussion about making transportation projects in a way that they can withstand the impacts of natural and human-induced disasters. Through this model, the stakeholders are encouraged to think about vulnerability and risk, and the factors that control them. Several new decision variables proposed for resilience can serve as a cornerstone for quantifying resilience in future optimization models and reshape the ENVISION rating system to improve the resilience section. This novel addition to the body of knowledge will help to remove the widespread ambiguity and confusion in understanding and quantifying the different dimensions of resilience.

The integrated sustainability and resilience optimization model (phase 4) provides one of the first efforts towards comprehensively capturing a realistic scenario associated with transportation projects where a focus on being environmentally friendly is maintained while also ensuring that any transportation project being planned, can withstand the impacts of disasters. The NSGA-II algorithm used in creating this model helps to analyze exponential number of datasets and find an optimal set of solutions while ensuring that these solutions do not represent local maxima or local minima. Usage of this model can benefit a project team in several phases namely, preliminary design phase, planning phase, construction phase, and operation and maintenance phase.

5.3 Limitations

The novel decision-making tool proposed in this research has a few limitations. It has been conceptualized using the ENVISION rating system assuming that transportation projects seeking to apply sustainability and resilience will use the ENVISION rating system. However, other rating systems such as Greenroads, INVEST, I-LAST, etc. exist within the US that provide guidance on the topics of sustainability and resilience. Furthermore, numerous transportation projects (roads and highways to be specific) do not use any rating system. As the stakeholders see the importance of sustainability and resilience with the adoption of the new ASCE infrastructure sustainability standard, which is based on the ENVISION rating system, the decision-making tool created in this research will be pivotal in achieving a higher level of sustainability and resilience. Furthermore, different countries across the world have different guidelines and rating systems which do not align with the ENVISION rating system, making it an arduous challenge to apply the decision-making model to global projects.

Another limitation of this research is the inaccessibility of datasets required to effectively use the decision-making model. There is no transparent exchange of data among the numerous roads and highway projects across the US. Often, these datasets are confidential or hard to access which makes it difficult for stakeholders to find a list of strategies that could be applied to achieve sustainability and resilience. Therefore, stakeholders seeking a higher level of sustainability and resilience in their projects need to prepare a list of strategies which can be fed as an input to the model proposed in this research.

The greenhouse gas (GHG) emissions calculation has been based on the Road Emissions Model (ROADEM) which has a set of parameters and inputs that define the amount of emissions associated with any strategy. However, accuracy of the GHG emissions calculation needs improvement as factors such as location, phase of project, etc. are not considered within ROADEM.

Lastly, models such as the one proposed in this research need buy-in from the transportation agencies and other stakeholders for it to be used widely across the US and around the world. The model currently exists as more than 6,000 lines of code in MATLAB. In the current state of the model, it is difficult for the model to be readily applied in the construction industry due to a lack of user-interface.

5.4 Future research

Though this research focusses on transportation projects, it can easily be applied to other infrastructure projects (water, energy, telecommunications, etc.). Additionally, the model is robust to be adapted for other rating system used across the world.

It is important to note that the data collection poses a severe challenge to the application of this optimization model, however, with recent developments being made to promote the creation of digital data repositories, models such as the one proposed in this research will be widely adopted in the construction industry. The dataset was created in Microsoft Excel which makes it user-friendly for state DOTs, contactors, and consultants to add data for their projects. Future studies can expand the excel database of strategies for different types of infrastructure projects.

Current study uses a Road Emissions Model to quantify the emissions associated with various inputs, which can be inaccurate as the model considers broader project information to provide a general idea of total emissions associated. A more accurate quantification of the greenhouse gas emissions (GHG emissions) can be pursued in another future study which use sets of strategies by using Life Cycle Assessment (LCA).

An easy-to-access user interface can be created rooted in the NSGA-II algorithm and the code created through this research which can help the stakeholders to use the decision-making model with ease. This development can make transportation agencies more inclined to use sustainability and resilience in their projects.

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