Bridging the Gap Between Used EV Batteries and Grid Storage

P.I. Bykov

March 20, 2024

Abstract

This study addresses the evaluation of repurposing used Electric Vehicle (EV) batteries for grid storage solutions in Sub-Saharan Africa, with a focus on Tanzania. Through financial modeling and environmental impact assessment, the research contrasts the sustainability and economic viability of employing repurposed EV batteries against traditional diesel generators. Factors such as energy consumption patterns, cost of electricity and diesel, inflation rates, and emission metrics are analyzed to forecast operational costs and environmental benefits over a three-year period. The findings reveal that power pack systems, constituted of repurposed EV batteries, significantly reduce total cost of ownership and operational expenses, while minimizing carbon and pollutant emissions.

Contents

Acronyms

EV Electric Vehicle

OEM Original Equipment Manufacturer

EOL End Of Life

PSS Power Swap System

CHEP Australian Company specializing in supply chain solutions

IISD International Institute for Sustainable Development

MHLNews Material Handling & Logistics News

SA Sustainability Assessment

CATL Contemporary Amperex Technology Co. Limited

BYD "Build Your Dreams" - Chinese automotive manufacturer

SK SK Group - South Korean company engaged in development, production, and sale of batteries

LFP Lithium Iron Phosphate

VPP Virtual Power Plant

DER Distributed Energy Resource

IEA International Energy Agency

UNDP United Nations Development Programme

HTE Human-Technical-Environmental assessment framework for enhancing sustainability research

GM General Motors

SSA Sub-Saharan Africa

NPV Net Present Value

WACC Weighted Average Cost of Capital

$\mathbf{CO_2}$ Carbon Dioxide

$\mathbf{NO_x}$ Nitrogen Oxides

PM Particulate Matter

HC Hydrocarbons

CO Carbon Monoxide

MJ Megajoule

kWh Kilowatt Hour

USD United States Dollar

ETR Ecological Threat Report

CPI Corruption Perceptions Index

GPI Global Peace Index

GTI Global Terrorism Index

SDGs Sustainable Development Goals

AfDB African Development Bank

WHO World Health Organization

IFC International Finance Corporation

1 Introduction

The literature review provides an operational definition of sustainability and an understanding of the scope of this project. Having covered the challenges in the realm of electric vehicles (EVs), we identified the general opportunities in the field. Since the ultimate aim is to formulate a recommendation that fulfils said sustainability definition, the next step is to define a case study with maximum potential to realise these opportunities. This potential will be defined in terms of a set of criteria, which will be applied to a high level view of the EV sphere to pinpoint the areas of interest.

2 Aims & Objectives

We aim to take a top-level view of the EV field to select a case study, which best aligns with the criteria and project scope, defined below.

Initial criteria are explicitly stated in the literature review, based on the four-pillar definition of sustainability. These will serve as a primary indicators of a case study's potential:

Fields which the case study is desired to span are:

- Battery Lifecycle Management
- Policy Frameworks
- Technological Innovations
- New Business Models
- Data Sharing and Transparency
- Ethical Mineral Extraction

The scope of the case study will be confined by:

- **Sufficient Complexity** to enable the application of at least one of the methods and tools outlined in the literature review. In other words, the case study will demonstrate a multiplicity of interdependent variables and a level of interaction that necessitates the application of the aforementioned methods. This includes the presence emergent concepts and significant interactions between technological, regulatory, economic, and environmental aspects.
- **Sufficient Transparency** to have significant confidence in the evaluation of uncertainties and quality of data in the quantification process. Here, we will choose to define transparency in terms of the level of conflict of interest. We assume that higher levels of conflict of interest contributes directly to the opacity of the field and decreases the precision of any conclusions made based on quantitative evaluation.

3 Additional Research

3.1 High Level Perspective

A high level overview is key to understanding the landscape of the field, before condensing to a specific case study. We will consider the main stakeholders in the EV supply chain and lifecycle understand their interplay.

The 6 main stakeholders were identified by looking at a current, industry-specific report by CHEP, providing data-driven insights into EV supply chain trends. Its relevance and credibility stems from CHEP's expertise in supply chain management: [1]

- **Original Equipment Manufacturers** (OEMs / Automakers)
- **Governments**
- **Mining & Extraction**
- **Battery Producers**
- **Logistics**
- **Energy Suppliers & Grids**
- **End Of Life (EOL) & Recycling**

The chronology and interdependencies of key stakeholders of the supply chain and EV lifecycle were established, presented in Figure 1. It captures the supply chain and lifecycle of EVs, initiating with the mining and extraction of raw materials. This lifecycle is supported by a logistics network that facilitates the flow of products throughout the chain. The government, while not depicted, exerts regulatory and oversight control over the entire process.

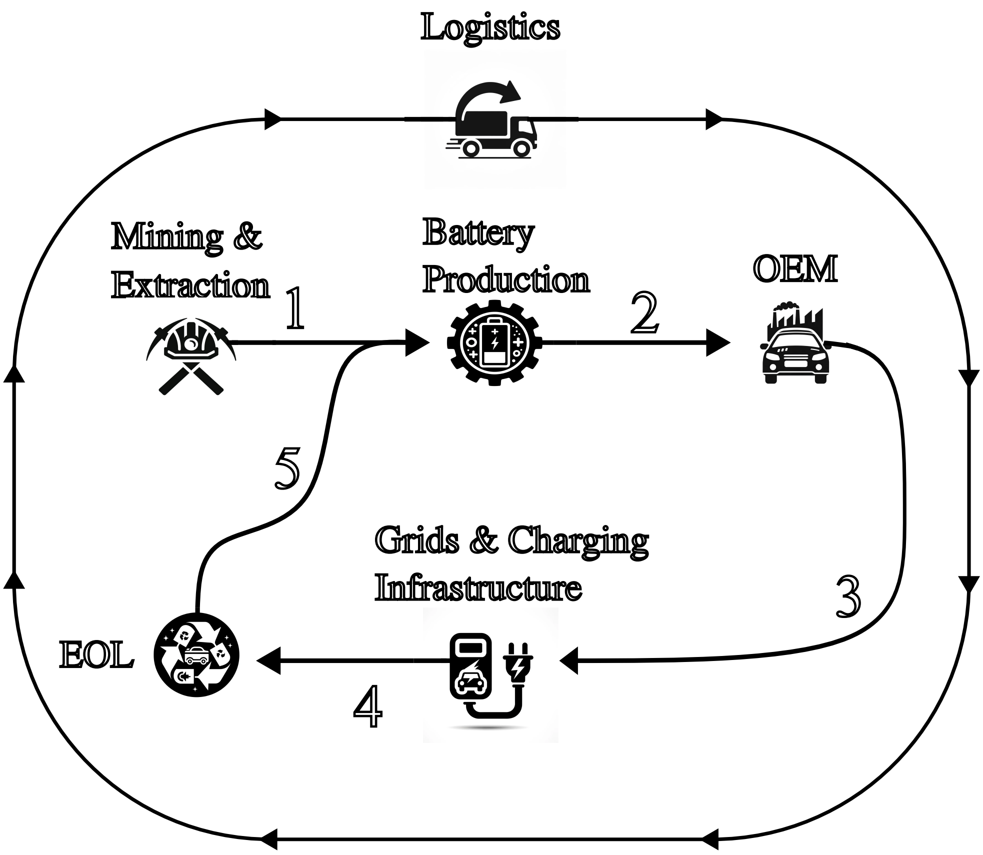

Figure 1: Simplistic supply chain and lifecycle flowchart for EVs

A general view of the EV supply chain and lifecycle can be formulated as follows:

1. Mining & Extraction supply the raw materials downstream.
2. Battery production supply the OEMs with batteries for EVs.
3. Manufactured EVs rely on Grids & Charging Infrastructure during their useful life.
4. EVs either undergo battery replacements are are disassembled. Either way, some EV parts are recycled during the EOL stage.
5. Recycled material rejoin the stream, alongside with the raw materials from Mining & Extraction.

3.2 Stakeholder Consideration

Relevant stakeholders are to be identified, initially filtering out those outside our scope. Mining & Extraction, Logistics, and Governance & Policy sectors are excluded:

- **Mining & Extraction**: Characterised by environmental challenges and conflicts of interest, with over 40% of internal conflicts between 1950 and 2009 linked to natural resource exploitation. [2].
- **Logistics**: Faces transportation cost management challenges, regulatory complexities, and increased supply chain complexity. [3, 4, 5].
- **Governance and Policy**: Its complexity and variability across geographies make it infeasible to consider in this project's scope.

Focus narrows to stakeholders with potential for concrete solutions:

- Original Equipment Manufacturers
- Battery Producers
- Energy Suppliers & Grids
- End-of-Life & Recycling

This simplifies system under consideration to Figure 2.

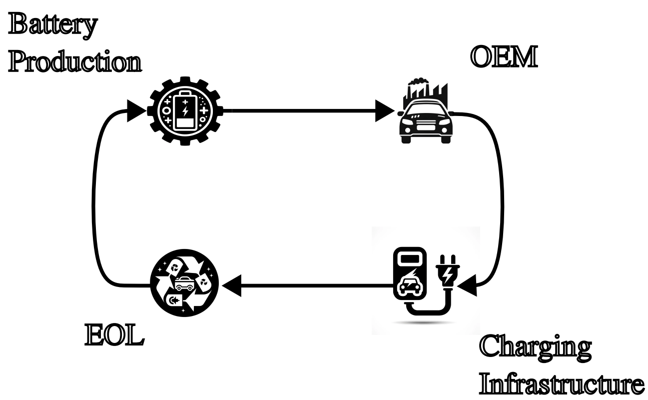

Figure 2: Condensed supply chain and lifecycle flowchart for EVs

Below, we consider each of the remaining stakeholders.

Battery Production Developments

Significant advancements by CATL, BYD, Panasonic, and SK Innovation in the EV battery market, including CATL's Qiji Energy battery swap system, showcase innovation and technological progress, with the potential to revolutionize the heavy-duty EV sector [6, 7, 8, 9, 10, 11, 12, 13].

Original Equipment Manufacturers (OEMs)

Tesla and BYD lead the expanding EV market, with significant contributions from other major manufacturers. NIO's global battery swap system (PSS) advancements and expansion into Europe with third-generation technology underscore innovation and user experience enhancement [14, 15, 16, 17, 18].

Grids & Charging Infrastructure

The integration of battery-based storage, especially lithium-ion technology, is crucial for the renewable energy transition, supporting grid stability, and enabling new revenue streams, with policies like the Inflation Reduction Act driving growth in storage capacity [19, 20, 21, 22, 23].

End-of-Life (EOL) & Recycling

The EU, China, and the US lead in EV battery recycling regulations and technology investment. The exploration of second-life applications for EV batteries in energy storage faces economic and technological development challenges [24, 25, 26, 27, 28].

4 The Case Study

4.1 Proposed Solution

Based on additional research, the work will focus on repurposing used EV batteries for grid storage, linking sustainability, technological innovation, new business models sand the circular economy. This aligns with enhancing EV and grid sustainability by extending EV batteries' life cycle beyond automotive use, restructuring EOL and Grids & Charging Infrastructure stages (see Figure 3).

EVs' environmental benefits rely on grid sustainability, whilst the grid's reliance on non-renewable sources poses a challenge. Integrating renewables like solar requires reliable storage, whilst used EV batteries offer substantial storage capacity. EV batteries are retired when their capacity drops to 70%-80%. Repurposing them for grid storage extends their useful life sustainably. The above relies on the surplus of used EV batteries, with around 900 kilotons available annually. About 4/5 of these may not be recycled.

Furthermore, the prospect of PSS adoption can speed up used EV battery availability for grid storage by standardizing specifications, easing the transition from automotive to stationary use. This promises fertile ground for integrating repurposed EV batteries, providing an economic and environmental synergy.

The work will evaluate lithium-ion battery applicability for grid storage and smaller domestic applications. Prevailing challenges urge alternatives to conventional power generators. Redirecting surplus EV batteries towards regions with energy shortages can mitigate costs and environmental impact.

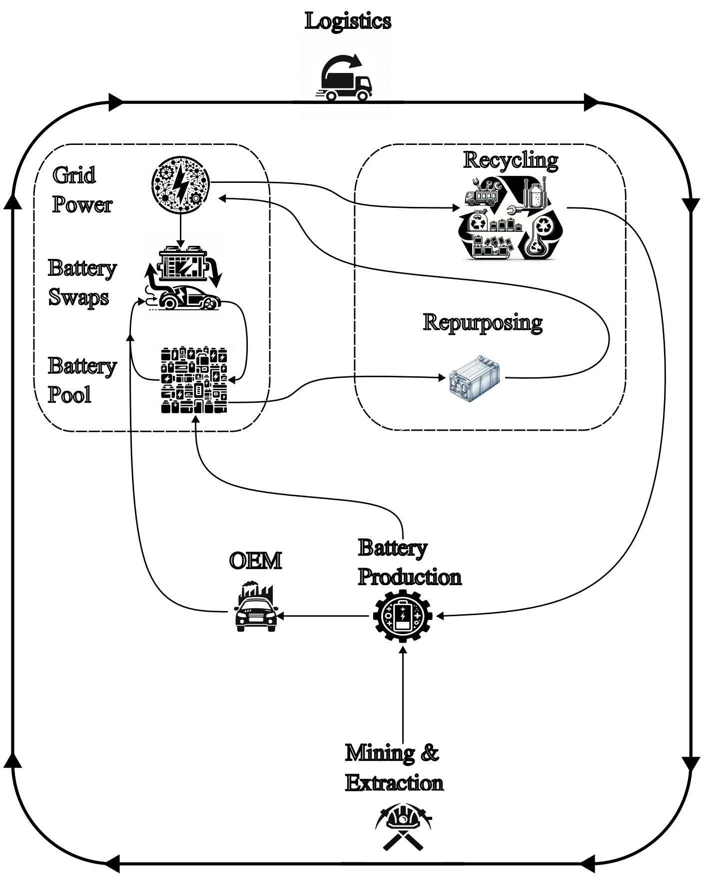

Figure 3: Proposed supply chain and lifecycle flowchart for EVs

4.2 Methodology

Due to the multidisciplinary nature of the case study, the work integrates various analytical tools and frameworks- critical to address the interactions within the EV ecosystem and the broader energy grid.

4.2.1 Tools

- **Python Battery Mathematical Modelling (PyBaMM):** will be instrumental in simulating battery performance and degradation, optimizing battery use in EVs.
- **PhD Thesis on EV Energy Management in Smart Grids:** Insights from this thesis will guide the integration of the batteries within smart grids.
- **Daniel Öster's GitHub Projects:** Practical applications and demonstrations from Öster's projects, including battery upgrades and emulators, will provide tangible references for battery lifecycle management and testing.
- **Human-Technical-Environmental (HTE) Framework:** will be employed to evaluate the interplay between human, technical, and environmental factors in the lifecycle management of EV batteries and their repurposing for grid storage. This framework facilitates a holistic sustainability assessment.
- **Sustainability Assessment (SA):** will be utilized to gauge the sustainability implications of integrating repurposed EV batteries into the grid.

4.2.2 Financial Modelling Framework

The stochastic financial model utilizes Python for numerical simulations, incorporating randomness in key variables to reflect real-world unpredictability. The Monte Carlo method will allow for the generation of possible scenarios to predict the performance and cost-effectiveness of energy solutions over time.

In the context of financial modelling, the following will be key to understand the future value of the proposal:

$$\text{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} \tag{1}$$

where NPV is the net present value, C_t is the net cash flow at time t, r is the discount rate, and T is the total number of periods.

4.2.3 Limitations & Anticipated Challenges

The work acknowledges potential challenges, including regulatory compliance, cost viability, supply chain disruptions, data privacy, and the geographical variability of political and environmental factors. A proactive approach, involving optimization of operational efficiencies, diversification of supply sources, and continuous update of model assumptions based on real-world data, will be adopted to mitigate these challenges.

5 Business Case

The below aims to evaluate the feasibility a business model that specializes in creating sustainable and efficient power backup systems utilizing repurposed EV batteries and solar energy integration. However, it's first key to understand the geographical context in which the solution will be applied.

5.1 Relevant Geographies

5.1.1 Introduction to Sub-Saharan Africa

Sub-Saharan Africa (SSA) tops the ranks of critical electricity access deficits, with over 80% of the world's population without electricity access in this region [29, 30].

SSA has the most pronounced electricity deficit, despite a per capita electricity consumption of 150 kWh, as reported by McKinsey. The frequent power outages average at nine occurrences per month, each lasting approximately 5.7 hours. Consequently, an annual deficit of 92340 kWh per capita can be estimated, amounting to 615.6 hours of electricity shortage per annum.

A deeper look reveals that about 580 million people lacked electricity access in 2019. In 2018, on-grid unmet demand was 8.83 terawatt-hours (TWh), rising to 42.9 TWh when including off-grid and unelectrified households. Additionally, a hypothetical 50% reduction in tariffs would further increase unmet demand to 21.46 TWh for on-grid and 55.53 TWh for off-grid users. This situation underscores the urgent need for enhanced electricity infrastructure and policies in the region. [31]

5.1.2 Costs due to Power Cuts

Power cuts in SSA result in economic, social, and environmental detriments, hindering the region's development. These issues obstruct progress towards sustainable development and necessitate urgent solutions.

Economic Impacts: Power unreliability disrupts key sectors, affecting manufacturing, agriculture, and services, with the World Bank estimating a potential 2-4% annual GDP growth in SSA with improved electricity reliability [29]. This instability deters investment and curtails business growth, perpetuating economic stagnation. Businesses face financial losses, with the African Development Bank reporting annual revenue losses of 4-5% due to outages, leading to reliance on costly backup solutions that diminish profitability and competitiveness [32].

Environmental Effects: The use of diesel generators releases over 40 million tonnes of CO2 annually, contributing to air pollution and climate change [33].

Societal Consequences: Inadequate electricity access impedes progress towards the SDGs by affecting healthcare, education, and economic opportunity, with the United Nations Economic Commission for Africa highlighting the disruption to healthcare and education [34]. Over 25% of healthcare facilities lack reliable electricity, impacting medical services and necessitating reliance on backup power, which diverts resources from patient care [35].

Climate Investment: Power supply unreliability undermines investor confidence, reducing SSA's appeal to both foreign and domestic investors and limiting economic growth and job creation, as noted by the International Finance Corporation [36].

5.1.3 Current Measures

The primary response to the inadequate and electricity supply results in the highest share of electricity output from generators globally, accounting for 80% of the world's diesel generator use [37]. The instability of oil prices and the environmental and health implications of diesel generators are motivating the transition to alternative energy solutions. Solar microgrids present a cleaner, more sustainable, and often more economical alternative to diesel generators, forming an additional niche for power storage applications [38].

5.2 Country Analysis

The selection of the SSA countries, is based on a range of indicies, outlined below. Firstly, 2023 data from the Ecological Threat Report (ETR) and the Corruption Perception Index (CPI) is taken, to find the 14 most favourable countries. On the consumer side, the selection based on ETR is based on the assumption that countries with higher ecological threats have more incentive to search for cleaner diesel generator alternatives. On the governance side, countries with lower corruption levels are more accommodating for new business. For the remaining selection of countries, the time series of the Global Peace (2008-2023) and the Global Terrorism (2011-2023) indices are considered. [39] [40] [41] [42]

Ecological Threat Report (ETR)

Quantifies the ecological risks faced by countries, integrating environmental and ecological data. Assesses threats such as water scarcity, food insecurity, exposure to natural disasters, and the impacts of climate change. It is constructed through the aggregation of indicators across several ecological domains. These indicators are normalized and weighted to reflect their relative importance to ecological stability, the overall ETR score for a country or region, ETR_n, is as follows:

$$ETR_n = \sum_{i=1}^{I} w_i \cdot e_{i,n}$$

where:

- w_i: weight of the i^{th} indicator,
- $e_{i,n}$: normalized score of the i^{th} indicator for region n,
- I: total number of indicators.

Corruption Perceptions Index (CPI)

Aggregates standardized scores from 13 surveys to measure perceptions of public sector corruption. The composite CPI score for country n, CPI_n, is:

$$CPI_n = \frac{1}{K} \sum_{k=1}^{K} x_{k,n}$$

where $x_{k,n}$ is the standardized score from the k^{th} source for country n, and K is the number of sources assessing the country. Scores range from 0 (highly corrupt) to 100 (very clean).

The consideration of ETR exposed that the only three countries with an index that is not one are South Africa (106), Botswana (84) and Ghana (74). These happen to be present in the 20 countries with least corruption, as per the CPI.

Global Peace Index (GPI)

Calculated using 23 indicators across three domains: Societal Safety and Security, Ongoing Domestic and International Conflict, and Militarization. The formula for a country's GPI score, GPI_n, is:

$$GPI_n = \sum_{i=1}^{23} w_i \cdot s_{i,n}$$

where w_i represents the weight of the i^{th} indicator, and $s_{i,n}$ is the normalized score of the i^{th} indicator for country n. This calculation enables a quantitative assessment of peace on a normalized scale from 1 to 5. Shown in Figure 4.

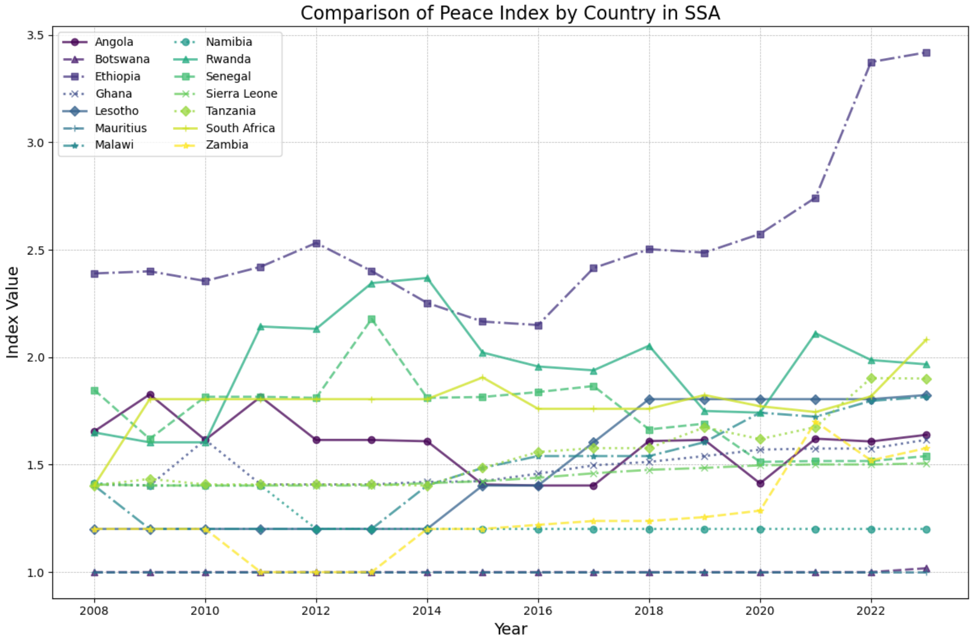

Figure 4: Global Peace Index time series across the selected Sub- Saharan countries

Global Terrorism Index (GTI)

Calculated using four main weighted indicators: number of terrorist incidents, fatalities, injuries, and extent of property damage. The GTI score, GTI_n, is:

$$GTI_n = \sum_{j=1}^{4} w_j \cdot I_{j,n}$$

where w_j is the weight for the j^{th} indicator and $I_{j,n}$ represents the value of the j^{th} indicator for country n. This score is subsequently adjusted through a five-year weighted average and transformed onto a 0–10 scale. Shown in Figure 5.

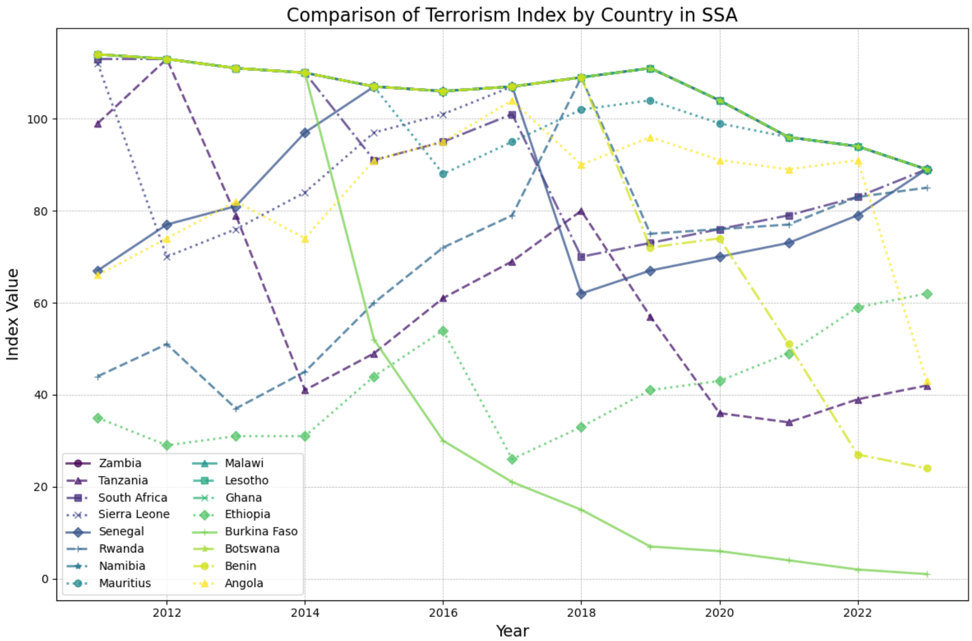

Figure 5: Global Terrorism Index time series across the selected Sub-Saharan countries

In both cases, there's significant difference in their variation. A chosen approach is to obtain the standard deviation for each index and select the countries with least volatility. Thus, we are left with 9 best candidates: Mauritius, Botswana, Sierra Leone, Ghana, Namibia, Angola, South Africa, Tanzania

5.2.1 Economic Growth & Stability

Another crucial aspect is economic growth and its stability. Without a sustainable economic upside. Using Figure 6 by McKinsey [43], validates the selection of Mauritius, Botswana, Sierra Leone, Ghana, Namibia, Angola, South Africa, Tanzania.

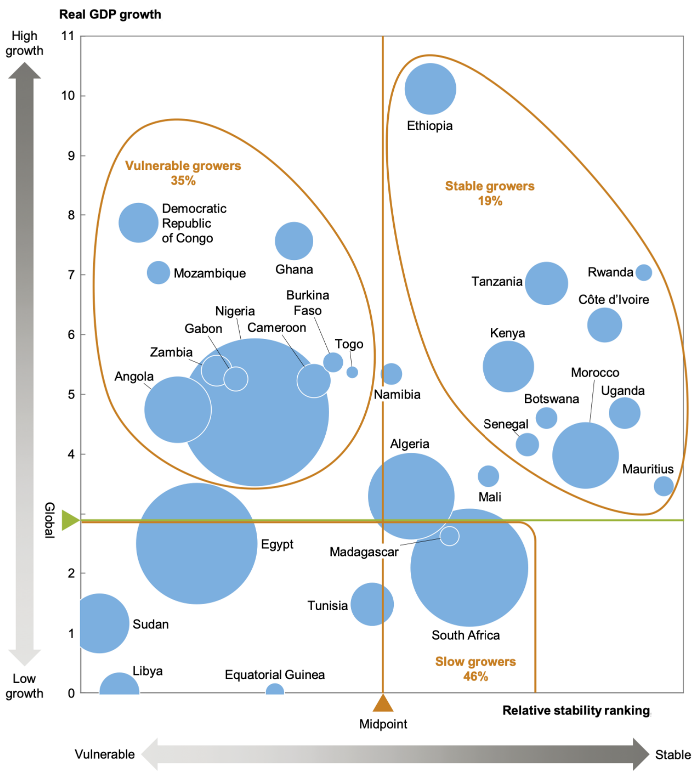

Figure 6: Economic growth with relative stability for African Countries. [43]

5.3 High-Level Logistics

Having clarified the geography, it is now possible to suggest a logistic network through which the proposed solution can be delivered:

1. **Collection and Transportation:** Aggregation of used EV batteries, retaining around 80% efficiency, from various global sources. These batteries will be transported to a central hub in South Africa, utilizing its well-established logistics network.

2. **Battery Repurposing:** The batteries will be refurbished into modular power packs at a specialized facility. This step is crucial for converting used EV batteries into effective energy storage systems for both grid-connected and off-grid use.

3. **Integration with Renewable Energy:** These power packs will be designed to integrate with renewable energy setups, particularly solar microgrids, to ensure a stable power supply in various regions, including remote areas.

4. **Distribution and Implementation:** The power packs will be distributed across SSA to businesses, homes, and public institutions, offering a reliable power source and reducing dependence on unstable grid electricity and polluting diesel generators.

5.4 System Overview

Based on the above analysis and data availability, the case study will be applied to an average hotel in Tanzania. The proposed solution is a system designed for energy storage and backup power supply using a repurposed EV battery pack, capable of interfacing with both the conventional electrical grid and a photovoltaic (PV) solar system, illustrated by Figure 7. The primary components and their interconnections are as follows:

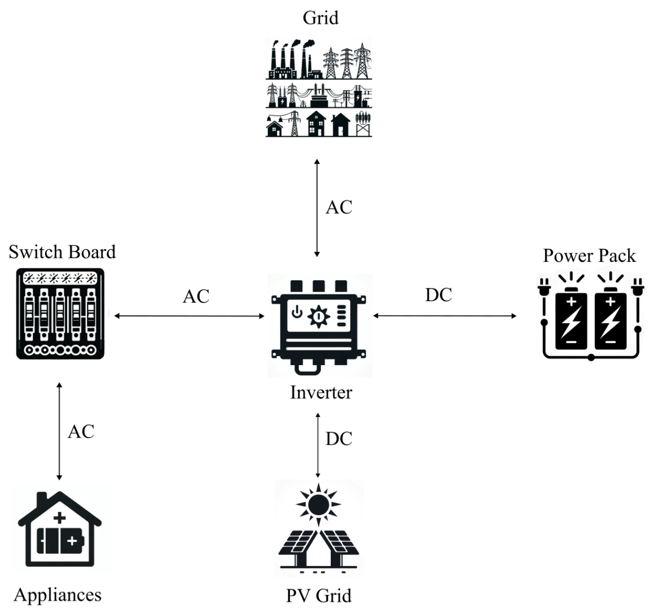

Figure 7: Schematic Layout of the System

- **Grid**: The conventional AC (alternating current) supply is the primary source of power for charging the Power Pack and supplying energy to the household under normal operating conditions.

- **Power Pack**: A used EV battery pack repurposed as an energy storage system stores electrical energy in the form of DC (direct current), used during power outages.

- **Inverter**: Firstly, it converts AC from the grid to DC to charge the Power Pack. Secondly, it inverts DC from the Power Pack (or PV grid) back to AC for household use when the grid power is unavailable.
- **PV Grid**: Generates DC power, either used to charge the Power Pack or converted to AC for direct use.
- **Switch Board**: The electrical distribution system, which receives AC power either from the grid or the inverter and distributes it to various appliances.
- **Appliances**: End-users of electricity.

The energy flow within this system can be described as follows:

1. Under normal conditions, the Grid supplies AC power to both the Switch Board for immediate consumption by Appliances and to the Inverter for charging the Power Pack.
2. The Inverter converts AC power to DC for charging the Power Pack. The PV Grid, when conditions allow (sufficient sunlight), generates DC power that can either be used to charge the Power Pack or converted to AC by the Inverter for immediate use.
3. In the event of a power cut or when the Grid is not supplying power, the Power Pack supplies DC power to the Inverter, which then converts it to AC and routes it to the Switch Board to maintain power supply to the Appliances.

5.4.1 Grid Characteristics

The electrical grid in Tanzania operates on a standard that is common among many countries, especially those previously under British influence. The characteristics of the grid are critical for selecting appropriate electrical equipment, including inverters, to ensure compatibility and safe operation. Below, we summarise the key electrical parametres of the Tanzanian grid, relevant for the choice of inverters:

Parameter	**Details**
Format	Single-phase for residential, three-phase for commercial and industrial
Frequency	50 Hz
Voltage (Single-phase)	230 volts
Voltage (Three-phase)	400 volts
Socket Type	British-style Type G
Socket Voltage/Frequency	230 V, 50 Hz

Table 1: Summary of Tanzanian Electricity Supply Characteristics, [44] [45]

5.4.2 Solar Energy Potential

The solar power potential is estimated based on the formula:

$$P = A \times G \times \eta$$

where P is the power generated in kilowatt-hours (kWh), A is the area in square metres (m^2), G is the solar irradiance in kilowatt-hours per square metre per day ($kWh/m^2/day$), and η is the efficiency of the PV cell.

For this estimation, the following assumptions are made:

- Average solar irradiance (G) in Tanzania: 4 - 7 kWh/m² [46]
- Efficiency of the PV cell (η): 17 - 20% [47]

The daily power generation potential per square metre of a PV cell in Tanzania can be calculated as follows:

$$P_{max} = 4 \cdot 0.17 = 0.68\ kWh/m^2$$
$$P_{min} = 7 \cdot 0.20 = 1.40\ kWh/m^2$$
$$P_{mean} \approx 1\ kWh/m^2$$

Given an average EV battery capacity of 6 kWh, 6 m^2, PV cells are likely to be sufficient to fully charge such a module within an hour at zero cost.

5.4.3 Power Pack Connection & PV Integration

The integration of used EV batteries into stationary power backup energy storage systems in conjunction with solar inverters, involves a detailed setup and connection process. Leaning on Daniel Öster's Battery Emulator project, we can draw up a setup for a large-scale application, as outlined in Figure 8. [48]

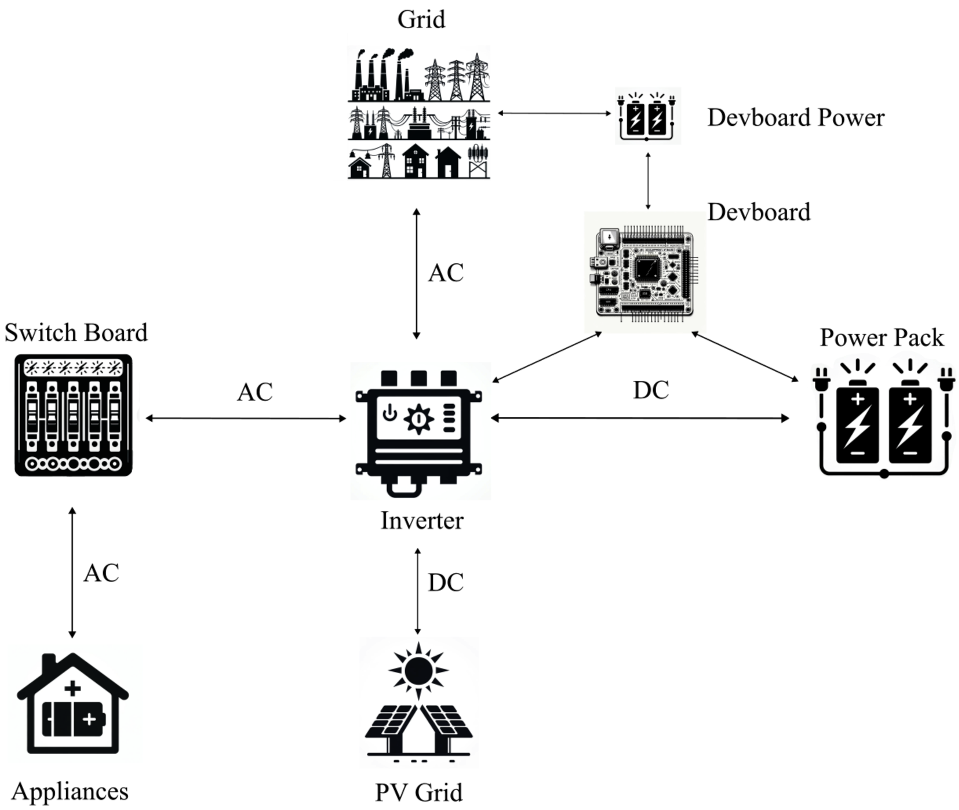

Figure 8: Detailed Schematic Layout of the System

Multiple hardware components are required to establish the connection:

LilyGo ESP32 T-CAN485 Development Board: ("Devboard" in Figure 8) The intermediary device facilitating communication between the EV battery and the hybrid inverter.

EV Battery: A pre-used EV battery, selected based on compatibility with the system.

Hybrid Inverter: "Fronius Gen24" or "GoodWe ET", capable of managing inputs from both solar panels and the grid, directing energy towards charging the battery or supplying power to loads.

Below is an outline of the connection logic:

Communication Interface Setup: A bidirectional communication setup is established between the EV battery management system (BMS) and the hybrid inverter using the LilyGo ESP32 T-CAN485 development board. This board interfaces the proprietary CAN bus of the EV battery with the standardised Modbus protocol employed by the hybrid inverter.

Power Connections: The hybrid inverter serves a dual function. It converts the AC power from the grid into DC to charge the EV battery, designated as the Power Pack. Concurrently, it inverts the DC output from the PV panels into AC, synchronising the energy supply with the grid's phase and frequency parametres.

Hybrid System Configuration:

- The Battery-Emulator's codebase is compiled and uploaded to the microcontroller unit (MCU) on the LilyGo board via the Arduino Integrated Development Environment (IDE), with user-specific configurations set in the `USER_SETTINGS.h` file, including battery type and communication settings.
- The operational logic embedded within the inverter's firmware is programmed to prioritise charging the Power Pack with PV-generated electricity, resorting to grid power during suboptimal solar generation while ensuring the maximal state of charge for blackout resilience.

Software Configuration: Compile and upload the Battery-Emulator software to the LilyGo board using the Arduino IDE, after configuring the IDE for ESP32 support and selecting battery type and system specifics in the `USER_SETTINGS.h` file.

Upon completing the hardware setup, the system is ready to use the EV battery as a dynamic storage solution. It switches between solar and grid energy for charging, based on real-time conditions and requirements.

The open-source software allows users to define operational parametres through the `USER_SETTINGS.h` file, influencing the battery and charger behaviour. Below are the adjustable settings.

Battery Capacity and Charging Limits

- `BATTERY_WH_MAX`: Defines the total energy capacity of the battery in Wh. Users must ensure not to exceed the inverter limit of 65,000 Wh for most inverters.
- `MAXPERCENTAGE`: Sets the upper charge limit as a percentage of the battery's capacity, e.g., 80%.
- `MINPERCENTAGE`: Sets the lower discharge limit as a percentage of the battery's capacity, e.g., 20%.
- `MAXCHARGEAMP` and `MAXDISCHARGEAMP`: Determine the maximum current in amps for battery charging and discharging.

Charger Settings

- `CHARGER_SET_HV`: The optimal high voltage for charging a 96s pack.
- `CHARGER_MAX_HV` and `CHARGER_MIN_HV`: Define the maximum and minimum permissible high voltage output of the charger.
- `CHARGER_MAX_POWER`: The maximum power output of the charger.
- `CHARGER_MAX_A` and `CHARGER_END_A`: The maximum current output and the final current for charging completion.

Network Settings for Web-Based Control

- `AccessPointEnabled`: Toggles the Wi-Fi access point functionality.
- `ssid` and `password`: Network credentials for connecting to the Wi-Fi network.
- `ssidAP` and `passwordAP`: Credentials for the Wi-Fi access point when enabled.
- `wifi_channel`: Selects the Wi-Fi channel, with '0' for automatic selection.

We can tailor the system's performance to our specific use case by adjusting these parametres to optimise battery lifespan and to integrate with particular inverters as well as to manage remote access.

6 Financial Modelling

This analysis focuses on the evaluation and comparison of generators and power packs, under operational and economic conditions in Tanzania. The work covers case study assumptions, modelling power cuts and service days, the impact of inflation on energy costs, detailed cost Modelling for generators and power packs, a comparative analysis of these energy solutions, and the calculation of NPV to assess the mid-term financial benefits of the solution. Python is used to implement these models to generate simulated data over a 3-year horizon, comparing the costs of diesel generators versus electricity from the grid, incorporating the factors below.

6.1 Energy Data

6.1.1 Energy Consumption

Average hotel energy consumption in the US ranges from 50-60 kWh. For the Tanzanian context, considering lower occupancies, simpler designs, and fewer amenities, we assume a range of 20-30 kWh per year, setting a base yearly consumption of 25,000 kWh.

6.1.2 Electricity Costs

Electricity pricing is set at a base rate of $0.094 per kWh, taking into account the current commercial rates as of June 2023. The analysis accommodates seasonal consumption patterns, which are influenced by climatic variations and tourist flux. The inflation rate for electricity costs is calculated based on historical data spanning 2017 to 2023.

6.1.3 Diesel Costs

Diesel cost modelling is crucial for understanding the financial implications of using diesel generators as a primary or backup energy source. The base cost of diesel is calculated using the formula:

$$\text{Diesel Cost per kWh} = \frac{\text{Base Diesel Cost per Litre}}{\text{Specific Energy of Diesel} \times \text{Efficiency} \times \text{Conversion Factor}} \tag{2}$$

Where:

- The base cost of diesel fuel is quantified at $1.32 per litre, with adjustments for local market fluctuations.
- The specific energy content of the diesel is considered to be 38 MJ/litre, assuming that this figure may vary with fuel quality.
- The diesel generator efficiency is estimated to be 30%, accounting for potential reductions in performance due to factors such as engine wear.

This results in a base diesel cost, allowing to consider diesel related expenses under variable inflation rates.

6.1.4 Emission Factors

The environmental impact can quantified by finding the emissions produced per kWh of diesel consumed. The emission factors include:

- Carbon Dioxide (CO_2): 2.68 kg per litre
- Nitrogen Oxides (NO_x): 6/1000 kg to 15/1000 kg per litre
- Particulate Matter (PM): 0.1/1000 kg per litre
- Hydrocarbons (HC): 0.6/1000 kg per litre
- Carbon Monoxide (CO): 3.5/1000 kg per litre.

6.2 Economic Data

6.2.1 Weighted Average Cost of Capital

The weighted average cost of capital (WACC) is set at a conventional 12%, mirroring the fiscal conditions within the SSA context.

6.2.2 Inflation

The annual inflation rate for Tanzania is assumed at 4.5%, influencing both the costs of energy and the evaluation of investments. Each cost component in the energy variables is adjusted for inflation as the annualised rates are applied to project the future expenses in present-day terms.

6.2.3 Generator Capital and Operational Expenditure

The assessment for generator use includes the capital expenditure of purchasing a 10kVA generator, with a mean price derived from current market rates. The operational costs encompass maintenance expenses, with an average annual spend of $1200, reflecting typical maintenance requirements. The efficiency loss of the generator is modelled at 2% per annum, with a total operational lifespan of 15 years.

6.2.4 Power Pack Systems

The cost analysis of power pack systems includes the acquisition cost of new battery modules and the discounted cost for used modules, assuming a lower - 30% - reduction in price for the latter. The capacity degradation and operational efficiency of the power packs are modelled, taking into account the reduced state of health in used modules. Maintenance costs for power packs are projected at 50% relative to those of diesel generators, accounting for the lower mechanical complexity and wear of battery storage systems.

6.2.5 Inflationary Adjustments

Each cost component in the energy variables is adjusted for inflation. The annualised rates are applied to project the future expenses in present-day terms. The annual inflation rate for Tanzania is assumed at 4.5%, influencing both the costs of energy and the financial evaluation of investment alternatives.

6.3 Variables' Models

6.3.1 Power Cuts

Here, we outline the methodology for simulating power cuts, a critical factor affecting energy reliability for businesses in Tanzania. Understanding the pattern and impact of these cuts is essential for planning and optimizing backup power solutions. The approach involves generating a stochastic model that simulates the occurrence and duration of power cuts over a specified period. This model is based on historical data and assumptions regarding the frequency and length of outages.

Assumptions

- Power cuts occur with a frequency of nine per month, influenced by infrastructure limitations and seasonal demands.
- The duration of each power cut follows a normal distribution ($\mu = 6h$), reflecting variability in the underlying causes and resolutions of outages.

Modelling

1. Initializing a matrix to record power cuts over the year, with columns representing the day of the year and the duration of the power cut.

2. For each month, randomly selecting days for power cuts and assigning a duration to each, drawn from a normal distribution around a specified mean and standard deviation.

3. Accumulating these values to construct a yearly profile of power cut frequency and duration.

Let N be the number of years, M the average number of power cuts per month, and D the average duration of a power cut. The duration d of each power cut is drawn from a normal distribution $d \sim \mathcal{N}(\mu, \sigma^2)$, where μ is the average duration and σ is the standard deviation.

The Modelling can be summarized by the equation:

$$\text{PowerCuts}_{\text{year}} = \sum_{\text{month}=1}^{12} \text{Random Selection}(\text{days}, M) \times \mathcal{N}(\mu, \sigma^2) \tag{3}$$

This model represents the unpredictability and impact of power cuts on business operations.

6.4 Service Days for Maintenance of Energy Systems

Here, we describe the methodology for modelling days on which maintenance is planned for energy systems. This involves creating a predictive model for scheduling maintenance based on historical data, operational demands, and the expected lifespan of the energy system components.

Assumptions

- Maintenance activities are scheduled periodically, with the timing influenced by the operational lifespan of the system components and past service history.

- The scheduling of service days follows a normal distribution around a mean interval, reflecting a balance between operational demands and maintenance needs.

Modelling

1. Determining the initial service day based on the installation date or the last service date of the energy system.

2. Using a normal distribution to model the variability in the interval between successive service days, capturing the stochastic nature of maintenance needs.

3. Generating a series of service days over the planning horizon to ensure that maintenance activities are appropriately spaced to maintain system reliability.

Let S denote the initial service day. The intervals between successive service days are modeled as random variables following a normal distribution with mean μ and standard deviation σ.

The sequence of service days can be represented as:

$$S_{i+1} = S_i + X, \quad X \sim \mathcal{N}(\mu, \sigma^2), \quad i = 1, 2, \ldots, N \tag{4}$$

where S_{i+1} is the day of the next service following S_i, and X is the interval between services drawn from the normal distribution.

6.5 Inflation

We look to outline the approach to Modelling inflation within the context of energy cost analysis. We aim to calculate the impact of inflation on energy costs over time, using a model that accounts for annual inflation rates and their compounding effect on prices.

Assumptions

- The annual inflation rate is applied uniformly across all energy costs, including electricity and diesel fuel, reflecting general economic conditions.
- Inflation rates are compounded annually, affecting future costs in a nonlinear manner.

Modelling

1. Identifying the base year costs for electricity and diesel fuel.
2. Applying the annual inflation rate to forecast future costs, compounding the inflation effect over the analysis period.
3. Generating an inflation-adjusted cost profile for the entire planning horizon, allowing for realistic financial planning and budgeting.

Let C_0 represent the base year cost of energy, and let r denote the annual inflation rate. The cost C_n in year n can be calculated using the formula:

$$C_n = C_0 \times (1 + r)^n \tag{5}$$

where n is the number of years into the future for which the cost is being calculated. This allows to plan for future costs, taking into account the diminishing purchasing power of money over time.

6.6 Integration of Variable Models

We compile the aforementioned variable models, such as power cuts, service days, electricity consumption, and inflation, to simulate energy data. We combine individual stochastic models to generate a dataset that reflects the power cuts, maintenance schedules, energy consumption patterns, and the impact of inflation on energy costs. We then estimate the operational costs of a generator, including initial purchase, maintenance, fuel consumption, and the impact of efficiency loss over time.

6.7 Energy Model

Assumptions

- The interaction between different variables, such as the frequency and duration of power cuts, the scheduling of service days, and the variability in energy consumption, is governed by stochastic processes.
- Inflation impacts energy costs annually, affecting the financial analysis of energy investments and operational expenses.

Modelling

1. Simulating power cuts and service days based on specified distributions to determine their frequency and timing throughout the year.
2. Calculating daily energy consumption, adjusting for seasonal variations and operational factors.

3. Applying inflation rates to project future energy costs, integrating these projections with the simulated operational data to forecast overall energy expenses.

4. Aggregating the results to create a comprehensive dataset that includes daily energy consumption, the occurrence of power cuts, maintenance schedules, and projected energy costs.

The integration of variable models can be conceptually represented as:

$$\text{DataModel} = f(\text{PowerCuts}, \text{ServiceDays}, \text{Consumption}, \text{Inflation}) \tag{6}$$

where f is a function that combines the outputs of individual models (PowerCuts, ServiceDays, Consumption, Inflation) to generate a unified dataset. This approach enables the simulation of complex, interdependent scenarios.

Considering daily operational and financial variables, the function can be succinctly represented as:

$$E_{\text{total}} = \sum_{t=1}^{Ndays} (C_{\text{energy}}(t) + C_{\text{pc}}(t) + C_{\text{sd}}(t)) \times I(t) \tag{7}$$

where:

- E_{total}: Total annual energy-related costs.
- $C_{\text{energy}}(t)$: Cost of energy consumption for day t.
- $C_{\text{pc}}(t)$: Additional costs incurred during power cuts on day t.
- $C_{\text{sd}}(t)$: Costs associated with service days on day t.
- $I(t)$: Daily inflation adjustment factor for day t.

This incorporates both consumption patterns and economic factors.

6.8 Generator Costs Model

Assumptions

- The generator has an operational lifespanof 15 years, after which it needs to be replaced.
- Generator efficiency decreases by 2% annually due to wear and tear.
- Maintenance costs and fuel prices are subject to inflation.

Modelling

1. Calculate the initial purchase cost of the generator.
2. Estimate annual maintenance costs, accounting for inflation.
3. Compute fuel consumption costs, adjusting for the generator's decreasing efficiency and inflation in fuel prices.
4. Accumulate these costs over the generator's lifespan to assess the total cost of operation.

Let $C_{purchase}$ be the initial purchase cost, $C_{maintenance}(t)$ the maintenance cost at time t, and $C_{fuel}(t)$ the fuel cost at time t, accounting for efficiency loss and inflation. The total cost C_{total} over a period T can be represented as:

$$C_{total} = C_{purchase} + \sum_{t=1}^{T} (C_{maintenance}(t) + C_{fuel}(t)) \tag{8}$$

where $C_{fuel}(t)$ is a function of the generator's efficiency at time t and the price of fuel, both of which may change over time. This is a view of both the upfront costs and the long-term operational expenses.

6.9 Power Pack Cost Model

Analogously to the above, we estimate the costs associated with power packs, including acquisition, maintenance, operational expenses and efficiency considerations.

Assumptions

- Power packs have a specified operational lifespan and efficiency, which degrades over time due to usage.
- The costs for maintenance and replacement of power packs are influenced by their operational lifespan and usage.
- Energy costs for charging power packs are accounted for, along with variations due to inflation.

Modelling

1. Calculating the initial purchase cost for power packs, considering options for new and used units.
2. Estimating the annual maintenance costs, taking into account the expected decrease in efficiency and the need for eventual replacement.
3. Assessing operational costs based on energy consumption for charging the power packs, adjusted for efficiency loss over time.
4. Summarizing these costs over the expected service life of the power packs to evaluate the total cost of ownership.

Let $C_{initial}$ denote the initial purchase cost, $C_{maintenance}$ the annual maintenance cost, and $C_{operational}(t)$ the operational cost at time t, which includes charging costs adjusted for efficiency. The total cost C_{total} over the lifespan L of the power pack can be expressed as:

$$C_{total} = C_{initial} + \sum_{t=1}^{L} (C_{maintenance} + C_{operational}(t)) \tag{9}$$

This encapsulates the comprehensive cost analysis and aids in comparing the cost-effectiveness of power packs against diesel generators, considering both short-term and long-term financial impacts.

6.10 Comparative Analysis and Savings Estimation

Now, we're prepared to compare the aggregate costs of generators and power packs for an energy-intensive business and to subsequently calculate the savings achieved by choosing the more cost-effective option. We aim to outline a comparison of cumulative costs associated with each energy solution over time, followed by an analysis of the potential savings.

Assumptions

- Both generators and power packs have specific operational lifespans, maintenance schedules, and efficiency factors that influence their overall costs.
- The inflation rate affects the cost of fuel for generators and electricity for charging power packs, impacting their operational costs.

Modelling

To find individual costs:

1. Aggregate the total costs for generators, including purchase, maintenance, and fuel costs, adjusted for efficiency loss over time.

2. Similarly, aggregate the total costs for power packs, considering purchase, maintenance, and operational (charging) costs.

3. Compare the cumulative costs over the same period to identify which option is more cost-effective.

To calculate the savings:

1. Determine the difference in cumulative costs between the two energy solutions over the analysis period.

2. Present the savings in a manner that clearly shows the financial advantage of choosing the more efficient option.

Let $C_{generator}(t)$ and $C_{powerpack}(t)$ represent the cumulative costs of using a generator and a power pack, respectively, up to time t. The savings $S(t)$ achieved by opting for the more efficient solution can be expressed as:

$$S(t) = C_{generator}(t) - C_{powerpack}(t) \tag{10}$$

where a positive value of $S(t)$ indicates savings when choosing power packs over generators. This approach provides a clear financial basis for choosing between generators and power packs.

6.11 Estimating Net Present Value of Savings

We can now obtain the NPV of savings, providing a basis for comparing the financial performance of different options over time. This involves discounting the projected savings from an energy solution back to their present value, using a specified discount rate that reflects the opportunity cost.

Assumptions

- Savings from the energy solution are estimated over a defined period, reflecting the operational lifespan of the assets.
- A constant discount rate is applied, which represents the WACC or an alternative rate that reflects the investor's required return.

Modelling

1. Estimate the annual savings generated by choosing one energy solution over another.

2. Discount these annual savings back to their present value using the chosen discount rate.

3. Sum the present values of all projected savings to obtain the NPV.

Let S_t represent the savings in year t, and r the discount rate. The NPV is calculated as:

$$\text{NPV} = \sum_{t=1}^{T} \frac{S_t}{(1+r)^t} \tag{11}$$

where T is the total number of years for which the savings are projected. This provides a standardized metric for evaluating and comparing the profitability of different investments, helping businesses make informed decisions.

6.12 Data Overview

Economic Data	
Annual Discount Rate (WACC)	12%
Annual Inflation for Tanzania	4.5%
Energy Data	
Base Cost of Diesel ($/L)	1.32
Specific Energy (MJ)	38
Efficiency for Diesel Engines	30%
Conversion from MJ to kWh	0.278
Base Cost of Diesel ($/kWh)	0.4165
Annual Diesel Inflation	3.5%
CO2 Emission (kg/L)	2.68
NOx Emission (min, kg/L)	0.006
NOx Emission (max, kg/L)	0.015
PM Emission (kg/L)	0.0001
HC Emission (kg/L)	0.0006
CO Emission (kg/L)	0.0003
Base Cost of Electricity ($/kWh)	0.094
Electricity Inflation (2017-2023)	$(0.094/0.0816)^{1/4}$
Generator Purchase Cost ($)	2200
Yearly Generator Maintenance Cost ($)	1200
Generator Efficiency Loss	2% per annum
Generator Lifetime (Years)	15
New Power Pack Purchase Cost ($)	1000
New Power Pack Capacity (kWh)	6.5
State of Health for Used Module	80%
Assumed Discount for Used Power Pack	50%
Assumed Used Power Pack Capacity (kWh)	5.2
Yearly Power Pack Maintenance Cost ($)	600
Power Pack Efficiency Loss	20% per annum
Number of Power Packs Needed	18

Table 2: Numerical Data Input for the Model

6.13 Results and Discussion

6.13.1 Generator Costs

The generator's initial investment is prominent in the cost graph, after which the expenses are relatively stable with slight upward gradient due to inflation. The costs experience high spikes, due to maintenance or component replacement, seen approximately every 100 days. The lower, far more frequent spikes reflect energy expenditures during power cuts. Figure 9.

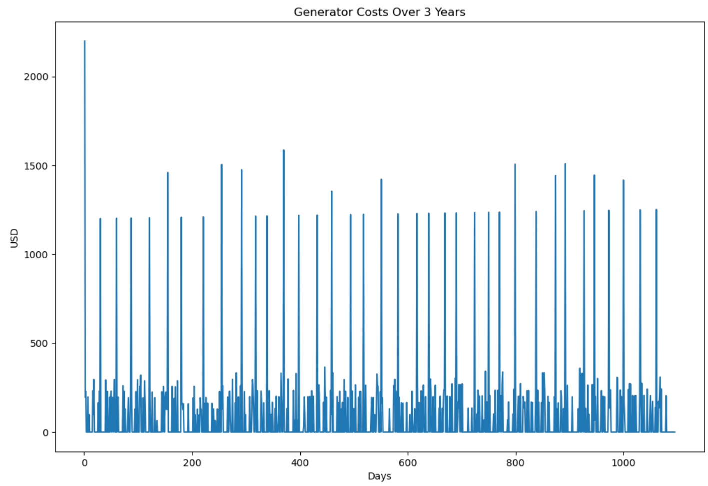

Figure 9: Generator Costs over 3 years

6.13.2 Power Pack Costs

Analogously to the generator costs, the power pack incurs costs at regular intervals, reflective of the replacement cycle and routine servicing, with a roughly-365 day period. The peak spikes in the expenditure graph correlate with power pack end-of-life and purchase of new power packs. Maintenance costs contribute to the smaller spikes. And the energy expenditures form the background "noise", seen at the lowest-value fluctuations. Figure 10.

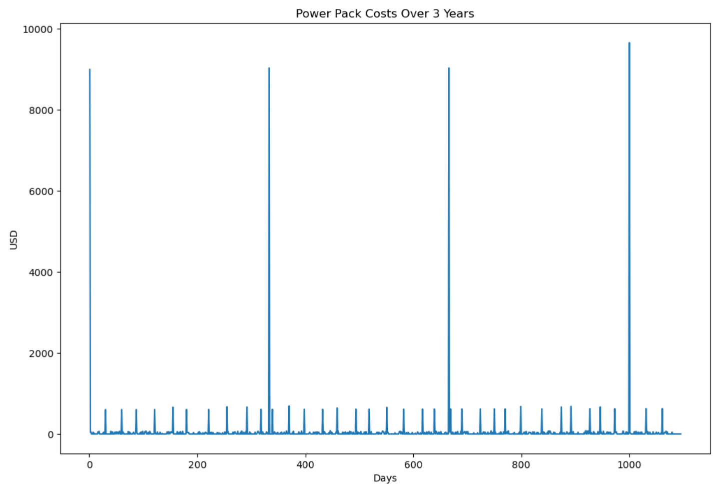

Figure 10: Power Pack Costs over 3 years

6.13.3 Cost Comparison

Cumulative costs for the power pack and generator start to diverge early in the time series. By day 1000, the generator's cumulative cost surpasses $100,000, while the power pack's cost is more than $30,000 lower. Figure 11.

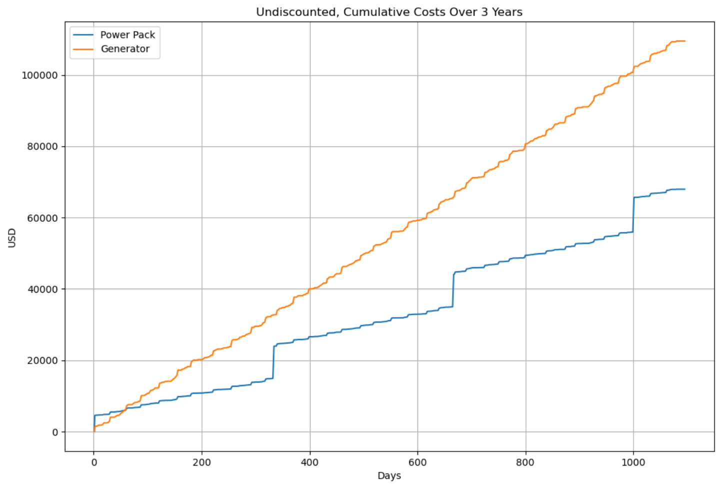

Figure 11: Projected costs of both the power pack use and diesel generator use over 3 years

6.13.4 Savings (Not Discounted)

Due to a relatively high power pack initial investment, there's a visible loss within the first two months, however the recovery is fast. After a two-month break-even, there's a steadily increasing gap between generator and power pack costs, reaching over $35,000 in savings by day 1000. This demonstrates a clear financial advantage of the power pack over the generator across the three-year period. Figure 12.

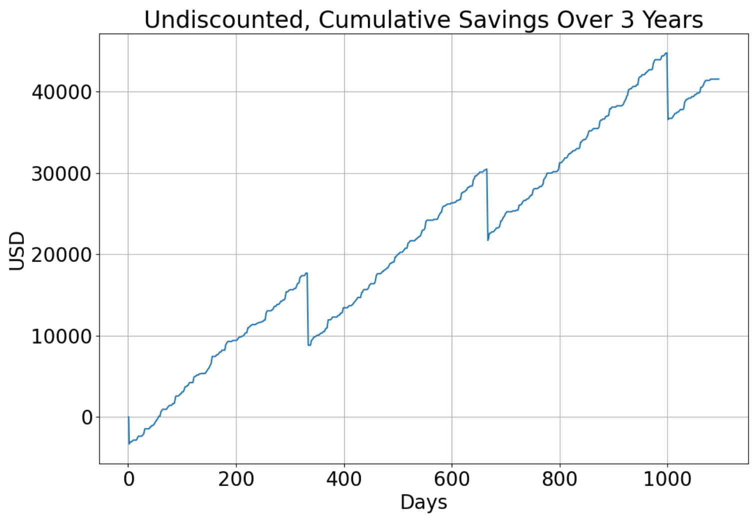

Figure 12: Projected savings from both the power pack use over diesel generator over 3 years. Obtained by subtracting power pack costs from diesel generator costs in Figure 11

6.13.5 Net Present Value

Factoring in a 12% annual discount rate, shows that the savings from the power pack amount to approximately escalating to nearly $30,000 by the end of year 3 - a reinforcement to the economic justification for the power pack investment. Figure 13.

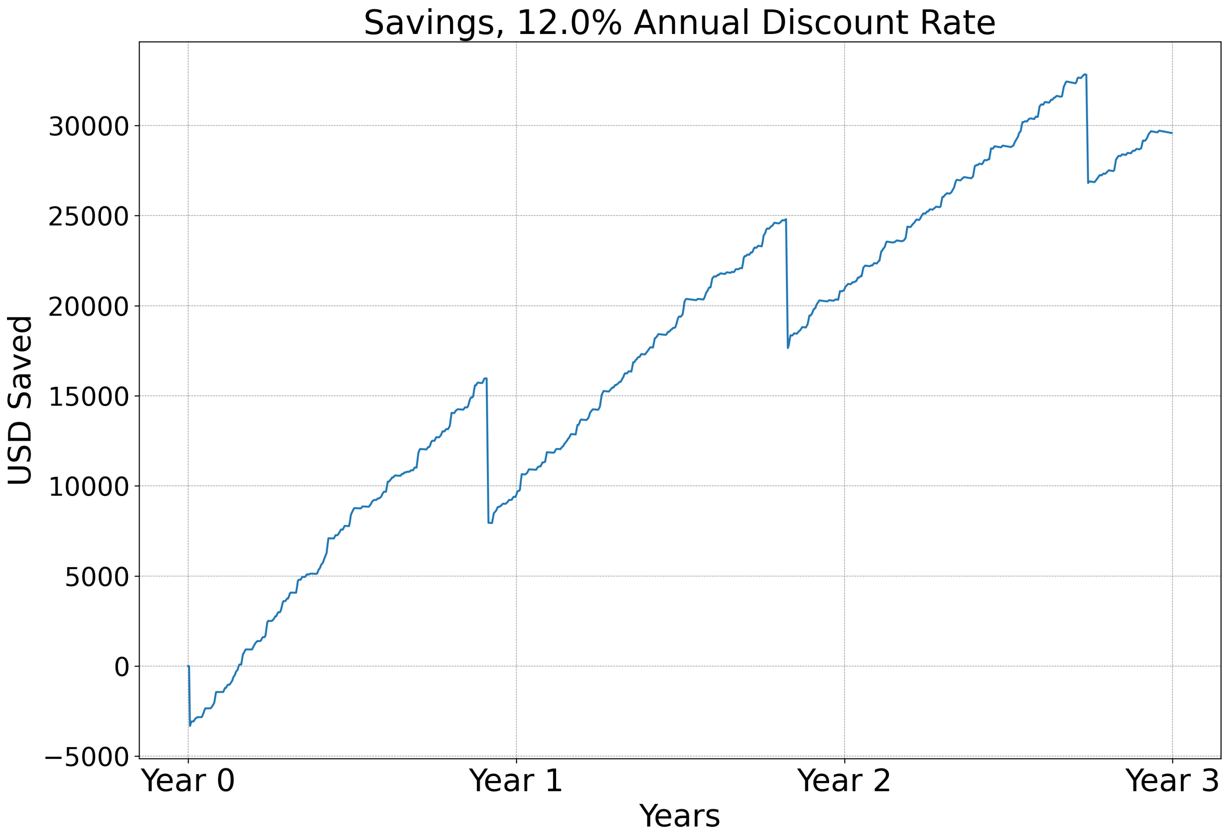

Figure 13: Savings due to power pack, discounted to present. Obtained by applying 12% WACC to Figure 12

6.13.6 Emissions

The environmental analysis reveals additional, ecological benefits of the power pack investment. Figure 14 shows the cumulative emissions of the of the key pollutants contained in diesel exhausts, summarised in Table 3.

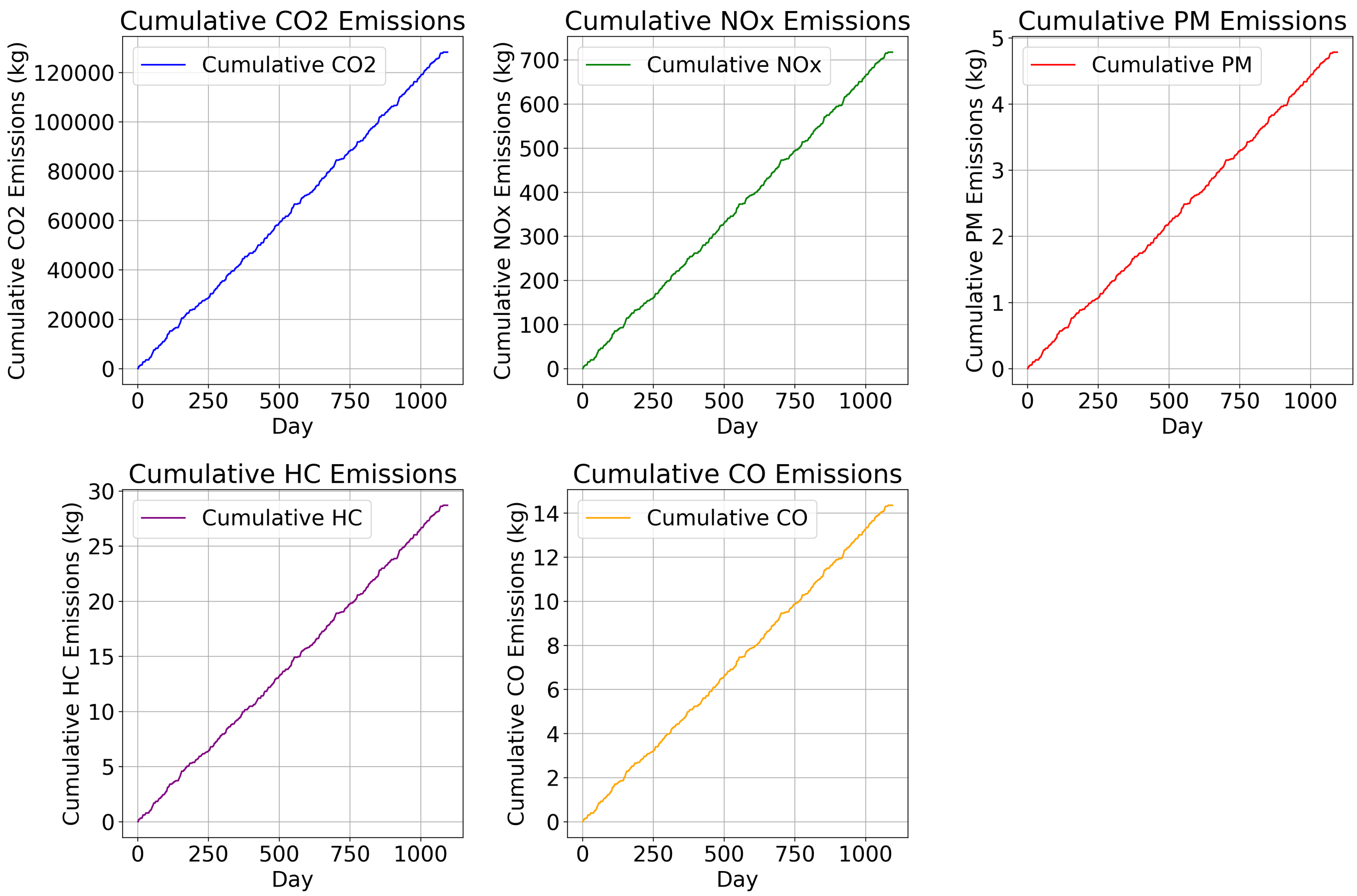

Figure 14: Emissions of diesel exhaust compounds over 3 years

Emissions Data	
CO2 Emission (tonnes)	120
NOx Emission (max, kg)	720
PM Emission (kg)	4.8
HC Emission (kg)	28
CO Emission (kg)	14

Table 3: Emissions Data over a 3-year Period of Generator Use

7 Conclusion

We investigated the feasibility and economic benefits of employing used EV batteries for grid storage purposes within Sub-Saharan Africa, with a focus on Tanzania. The approach encompassed an extensive financial analysis alongside an environmental assessment. This provided a significant comparison between the use of diesel generators and the innovative application of power pack systems derived from repurposed EV batteries.

The insights gained from the investigation underscore the significant economic incentives favoring the adoption of power pack systems over traditional diesel generators. The reduced total cost of ownership and operational expenses across a span of three years was shown for the suggested alternative. The savings due to the implementation of power packs, approximate a compelling reduction nearing $30,000 by the end of the third year. This finding not only highlights the economic viability of this alternative but also emphasizes its contribution towards environmental conservation, evidenced by a significant decrease in emissions of CO_2, NO, PM, HC, and CO, aligning with overarching sustainability objectives.

Nevertheless, this study is limited, notably in the context of the accessibility and condition of used EV batteries, adherence to regulatory frameworks, and the scalability of power pack systems across diverse geopolitical and economic landscapes within Sub-Saharan Africa.

Overall, the strategy of repurposing used EV batteries for grid storage emerges as a viable pathway towards bolstering energy security, diminishing the dependency on fossil fuels, and propelling sustainable development efforts in the region. The economic and environmental advantages shown advocate for further examination and endorsement by policy framers, industry stakeholders to exploit the potential of this solution.

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8 Appendix

A Country Analysis

TargetCountries

March 20, 2024

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
Intel MKL WARNING: Support of Intel(R) Streaming SIMD Extensions 4.2 (Intel(R)
SSE4.2) enabled only processors has been deprecated. Intel oneAPI Math Kernel
Library 2025.0 will require Intel(R) Advanced Vector Extensions (Intel(R) AVX)
instructions.
Intel MKL WARNING: Support of Intel(R) Streaming SIMD Extensions 4.2 (Intel(R)
SSE4.2) enabled only processors has been deprecated. Intel oneAPI Math Kernel
Library 2025.0 will require Intel(R) Advanced Vector Extensions (Intel(R) AVX)
instructions.
```

[2]:
```
SSA_countries = [
    "Angola", "Benin", "Botswana", "Burkina Faso", "Burundi", "Cabo Verde",␣
 ↪"Cameroon", "Central African Republic",
    "Chad", "Comoros", "Congo", "Democratic Republic of the Congo", "Djibouti",␣
 ↪"Equatorial Guinea", "Eritrea",
    "Eswatini", "Ethiopia", "Gabon", "Gambia", "Ghana", "Guinea",␣
 ↪"Guinea-Bissau", "Ivory Coast", "Kenya",
    "Lesotho", "Liberia", "Madagascar", "Malawi", "Mali", "Mauritania",␣
 ↪"Mauritius", "Mozambique", "Namibia",
    "Niger", "Nigeria", "Rwanda", "Sao Tome and Principe", "Senegal",␣
 ↪"Seychelles", "Sierra Leone", "Somalia",
    "South Africa", "South Sudan", "Sudan", "Tanzania", "Togo", "Uganda",␣
 ↪"Zambia", "Zimbabwe"
]
```

1 Corruption Perception Index (CPI)

[3]:
```
df = pd.DataFrame(pd.read_excel("CPI.xlsx")) # corruption perception index

# Filter out sub-Saharan African countries
CPI_SSA = df[df['Country '].isin(SSA_countries)]
CPI_SSA = CPI_SSA.reset_index().drop('index', axis = 1)
CPI_SSA = CPI_SSA.sort_values('Index', ascending = False)
```

```
CPI_SSA.head(3)
```

[3]:
```
      Country  Index
0  Seychelles     71
1  Cabo Verde     64
2    Botswana     59
```

2 Global Terrorism Index (GTI) Time Series

[4]:
```
# global terrorism indeces over the years

df23 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2023"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df22 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2022"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df21 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2021"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df20 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2020"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df19 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2019"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df18 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2018"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df17 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2017"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df16 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2016"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df15 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2015"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df14 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2014"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
df13 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
 ↪sheet_name="2013"))[['Country', 'rank']].sort_values('Country', ascending =␣
 ↪False)
```

```
df12 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
↪sheet_name="2012"))[['Country', 'rank']].sort_values('Country', ascending =␣
↪False)
df11 = pd.DataFrame(pd.read_excel("Copy of GTI_PublicReleaseData_2024.xlsx",␣
↪sheet_name="2011"))[['Country', 'rank']].sort_values('Country', ascending =␣
↪False)
```

[5]:

```
# Filter out sub-Saharan African countries

df23 = df23[df23['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2023'}, axis = 1)
df22 = df22[df22['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2022'}, axis = 1)
df21 = df21[df21['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2021'}, axis = 1)
df20 = df20[df20['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2020'}, axis = 1)
df19 = df19[df19['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2019'}, axis = 1)
df18 = df18[df18['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2018'}, axis = 1)
df17 = df17[df17['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2017'}, axis = 1)
df16 = df16[df16['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2016'}, axis = 1)
df15 = df15[df15['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2015'}, axis = 1)
df14 = df14[df14['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2014'}, axis = 1)
df13 = df13[df13['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2013'}, axis = 1)
df12 = df12[df12['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2012'}, axis = 1)
df11 = df11[df11['Country'].isin(SSA_countries)].reset_index().drop('index',␣
↪axis = 1).rename({'rank':'2011'}, axis = 1)
```

[6]:

```
# Concatenate the DataFrames along the rows
GTI_SSA = pd.concat([df11, df12['2012'], df13['2013'], df14['2014'],␣
↪df15['2015'], df16['2016'], df17['2017'], df18['2018'], df19['2019'],␣
↪df20['2020'], df21['2021'], df22['2022'], df23['2023']], axis = 1)

# Reset index to ensure a continuous numerical index
GTI_SSA.reset_index(drop=True, inplace=True)

# Display the combined DataFrame
GTI_SSA.head()
```

[6]:
```
     Country  2011  2012  2013  2014  2015  2016  2017  2018  2019  2020  2021  \
0   Zimbabwe   114   113   111   110   107   106   107   109   111   104    96
1     Zambia   114   113   111   110   107   106   107   109   111   104    96
2     Uganda    27    33    43    55    57    69    75    86    92   104    45
3       Togo   114   113   111   110   107   106   107   109   111   104    77
4   Tanzania    99   113    79    41    49    61    69    80    57    36    34

   2022  2023
0    94    89
1    94    89
2    49    27
3    30    25
4    39    42
```

3 Global Peace Index (GPI) Time Series

[7]:
```python
GPI = pd.DataFrame(pd.read_excel("Copy of␣
↪GPI-2023-overall-scores-and-domains-2008-2023.xlsx", sheet_name = "Ongoing␣
↪Conflict"))
```

[8]:
```python
# Filter out sub-Saharan African countries
GPI_SSA = GPI[GPI['Country'].isin(SSA_countries)]
GPI_SSA = GPI_SSA
GPI_SSA.head(3)
```

[8]:
```
     Country   2008   2009   2010   2011   2012   2013   2014   2015   2016  \
1     Angola  1.655  1.827  1.615  1.816  1.615  1.615  1.609  1.408  1.403
9    Burundi  2.349  2.304  2.315  2.055  2.039  2.028  2.029  2.027  2.496
11     Benin  2.208  2.208  2.208  2.208  2.208  2.006  2.006  1.407  1.430

     2017   2018   2019   2020   2021   2022   2023
1   1.403  1.610  1.615  1.413  1.621  1.608  1.639
9   2.366  2.350  2.376  2.513  2.456  2.653  2.267
11  1.458  1.462  1.490  2.117  1.749  1.740  1.763
```

4 Ecological Threat Report (ETR)

[9]:
```python
ETR = pd.DataFrame(pd.read_excel("Copy of ETR_Public_Release_Data_2023.xlsx",␣
↪sheet_name = "Overall Scores"))
ETR = ETR.drop('ETR Score', axis = 1)
```

[10]:
```python
# Filter out sub-Saharan African countries
ETR_SSA = ETR[ETR['Country'].isin(SSA_countries)]
ETR_SSA = ETR_SSA.sort_values('ETR Rank', ascending = False)
ETR_SSA = ETR_SSA.reset_index()
```

```
ETR_SSA = ETR_SSA.drop('index', axis = 1)
ETR_SSA.head()
```

[10]:

	Country	ETR Rank
0	South Africa	106
1	Botswana	87
2	Ghana	74
3	Somalia	1
4	Malawi	1

5 Selecting Top 10 from CPI and ETR

[11]:
```
CPI_SSA.sort_values('Index', ascending = False )
```

[11]:

	Country	Index
0	Seychelles	71
1	Cabo Verde	64
2	Botswana	59
3	Rwanda	53
4	Mauritius	51
5	Namibia	49
6	Sao Tome and Principe	45
7	Benin	43
8	Ghana	43
9	Senegal	43
10	Burkina Faso	41
11	South Africa	41
12	Tanzania	40
13	Lesotho	39
14	Ethiopia	37
15	Gambia	37
16	Zambia	37
17	Sierra Leone	35
18	Malawi	34
19	Angola	33
20	Niger	32
21	Kenya	31
22	Togo	31
23	Djibouti	30
24	Eswatini	30
25	Mauritania	30
26	Gabon	28
27	Mali	28
28	Cameroon	27
29	Guinea	26
30	Uganda	26

```
31                        Liberia     25
32                     Madagascar     25
33                     Mozambique     25
34                        Nigeria     25
35       Central African Republic     24
36                       Zimbabwe     24
37                          Congo     22
38                  Guinea-Bissau     22
39                        Eritrea     21
40                        Burundi     20
41                           Chad     20
42                        Comoros     20
43   Democratic Republic of the Congo 20
44                          Sudan     20
45              Equatorial Guinea     17
46                    South Sudan     13
47                        Somalia     11
```

[12]:
```python
ETR_SSA.sort_values('ETR Rank', ascending = False )
```

[12]:
```
                              Country  ETR Rank
0                        South Africa       106
1                            Botswana        87
2                               Ghana        74
44                         Madagascar         1
25                               Mali         1
26                              Benin         1
27                       Burkina Faso         1
28           Central African Republic         1
29                           Cameroon         1
30   Democratic Republic of the Congo         1
31                            Comoros         1
32                         Cabo Verde         1
33                           Djibouti         1
34                            Eritrea         1
24                         Mozambique         1
36                              Gabon         1
37                             Guinea         1
38                             Gambia         1
39                      Guinea-Bissau         1
40                  Equatorial Guinea         1
41                              Kenya         1
42                            Liberia         1
43                            Lesotho         1
35                           Ethiopia         1
23                             Angola         1
22                          Mauritius         1
```

```
11                     Sierra Leone          1
3                           Somalia          1
4                            Malawi          1
5                           Namibia          1
6                             Niger          1
7                           Nigeria          1
8                            Rwanda          1
9                             Sudan          1
10                          Senegal          1
12                         Eswatini          1
21                         Zimbabwe          1
13                      South Sudan          1
14                          Burundi          1
15                       Seychelles          1
16                             Chad          1
17                             Togo          1
18                         Tanzania          1
19                           Uganda          1
20                           Zambia          1
45                       Mauritania          1
```

Only South Africa, Botswana and Ghana has non-one enviromental threat index. The rest are one.

[13]:
```
N = 20

CPI_SSA_topN = CPI_SSA.sort_values('Index', ascending = False )[:N]

selection = list(CPI_SSA_topN['Country '])
```

The non-one SSA countries are included in the top 25 corruption perception index. Hence we can simply select the top N countries from CPI.

[14]:
```
selection
```

[14]:
```
['Seychelles',
 'Cabo Verde',
 'Botswana',
 'Rwanda',
 'Mauritius',
 'Namibia',
 'Sao Tome and Principe',
 'Benin',
 'Ghana',
 'Senegal',
 'Burkina Faso',
 'South Africa',
 'Tanzania',
 'Lesotho',
```

```
 'Ethiopia',
 'Gambia',
 'Zambia',
 'Sierra Leone',
 'Malawi',
 'Angola']
```

6 Working with Time Series: GTI

[15]:
```
GTI_SSA_1 = GTI_SSA[ GTI_SSA['Country'].isin(selection) ]
GTI_SSA_1 = GTI_SSA_1.reset_index(drop=True)
```

6.1 As of 2023

[16]:
```
GTI_SSA_23 = GTI_SSA_1[ GTI_SSA_1['Country'].isin(selection) ][['Country',␣
 ↪'2023']]
```

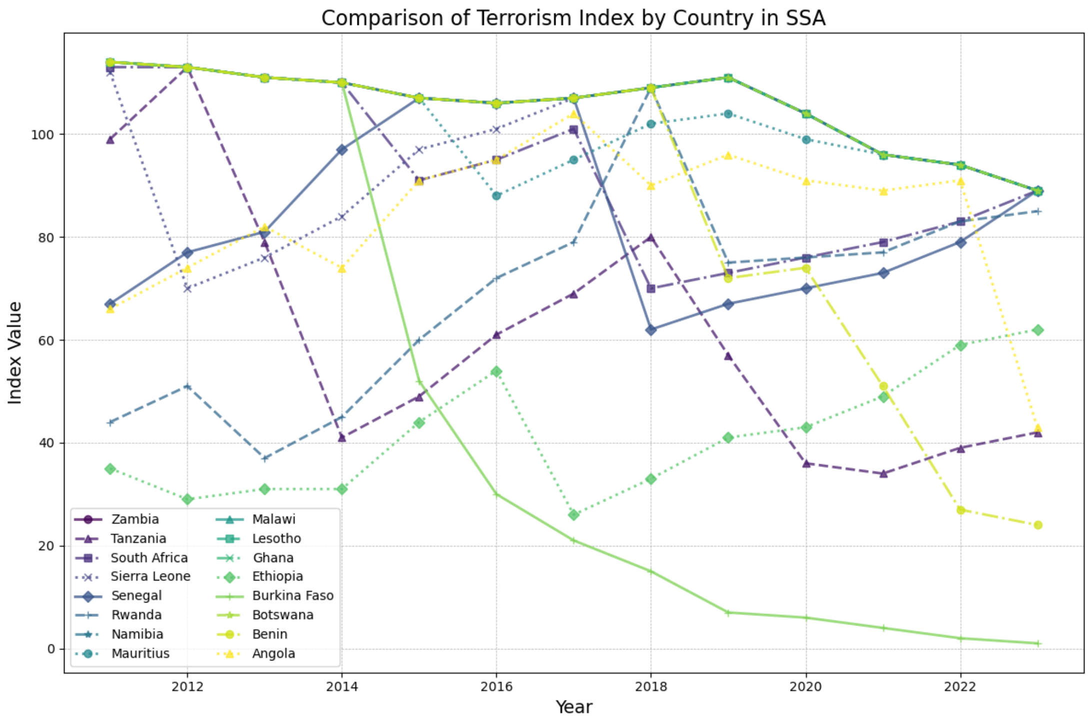
[17]:
```
GTI_SSA_23
```

[17]:
```
         Country  2023
0         Zambia    89
1       Tanzania    42
2   South Africa    89
3   Sierra Leone    89
4        Senegal    89
5         Rwanda    85
6        Namibia    89
7      Mauritius    89
8         Malawi    89
9        Lesotho    89
10         Ghana    89
11      Ethiopia    62
12  Burkina Faso     1
13      Botswana    89
14         Benin    24
15        Angola    43
```

6.2 Dynamics

[18]:
```
t = np.arange(2011, 2024)  # Time range

plt.figure(figsize=(12, 8))  # Adjust figure size for better visibility

# Define a list of line styles and markers to cycle through
line_styles = ['-', '--', '-.', ':']
```

```
markers = ['o', '^', 's', 'x', 'D', '+', '*']
colors = plt.cm.viridis(np.linspace(0, 1, len(GTI_SSA_1)))  # Use a colormap␣
↪for diverse colors

for i, (line_style, marker) in enumerate(zip(line_styles * len(markers), np.
↪tile(markers, len(line_styles)))):
    if i >= len(GTI_SSA_1):  # Check to prevent index error if more styles/
↪markers than countries
        break
    country = GTI_SSA_1['Country'][i]
    vals = list(GTI_SSA_1.iloc[i][1:])
    plt.plot(t, vals, marker=marker, linestyle=line_style, color=colors[i],␣
↪alpha=0.75, linewidth=2, label=country)

plt.title('Comparison of Terrorism Index by Country in SSA', fontsize=16)  #␣
↪Title with increased font size
plt.xlabel('Year', fontsize=14)  # X-axis label with increased font size
plt.ylabel('Index Value', fontsize=14)  # Y-axis label with increased font size
plt.legend(loc='best', ncol=2)  # Show legend with two columns to save space
plt.grid(True, which='both', linestyle='--', linewidth=0.5)  # Enhanced grid␣
↪visibility
plt.tight_layout()  # Adjust layout to fit everything
plt.show()
plt.savefig('GTI')
```



<Figure size 640x480 with 0 Axes>

[19]:
```
N =14
GTI_SSA_stats = GTI_SSA_1.set_index('Country').transpose().describe()
GTI_SSA_stats = GTI_SSA_stats.loc['std'].sort_values()[:14]
GTI_SSA_stats
```

[19]:
```
Country
Zambia           7.763326
Namibia          7.763326
Malawi           7.763326
Lesotho          7.763326
Ghana            7.763326
Botswana         7.763326
Mauritius        8.947855
Ethiopia        11.827825
Sierra Leone    13.334455
South Africa    15.845812
Angola          16.018819
Senegal         16.305182
Rwanda          20.287043
Tanzania        25.254093
Name: std, dtype: float64
```

[20]:
```
selection = list(GTI_SSA_stats.index)
```

7 Working with Time Series: GPI

[21]:
```
GPI_SSA_1 = GPI_SSA[ GPI_SSA['Country'].isin(selection) ]
GPI_SSA_1 = GPI_SSA_1.reset_index(drop=True)
```

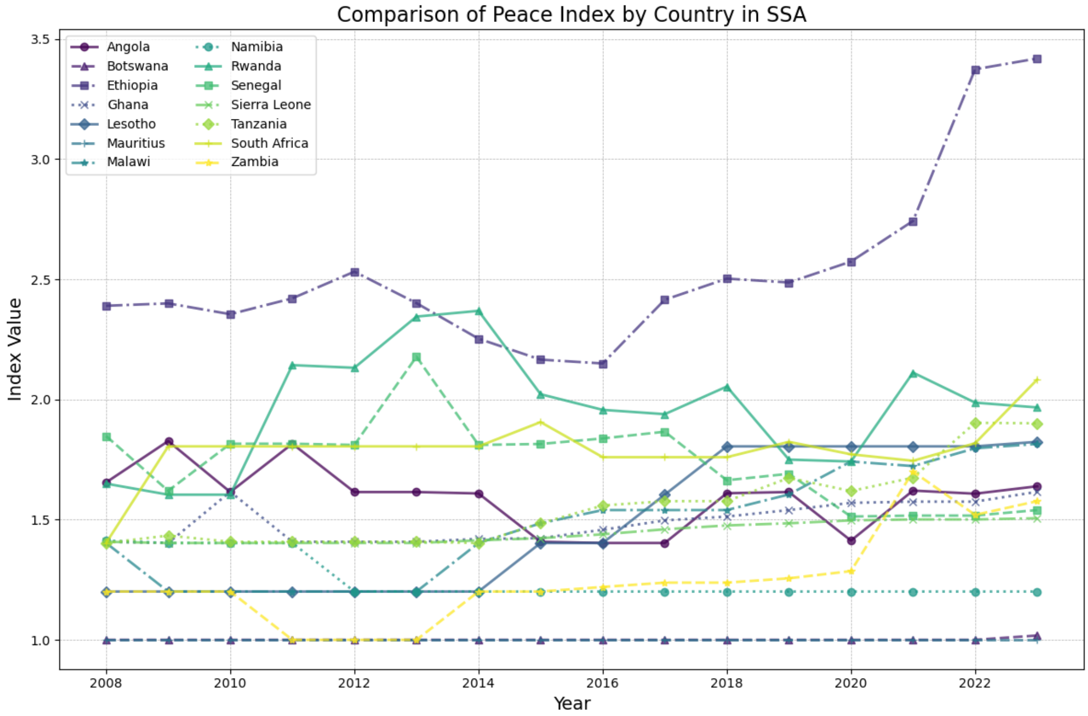
[22]:
```
GPI_SSA_1
```

[22]:
```
         Country   2008   2009   2010   2011   2012   2013   2014   2015  \
0         Angola  1.655  1.827  1.615  1.816  1.615  1.615  1.609  1.408
1       Botswana  1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
2       Ethiopia  2.390  2.400  2.355  2.421  2.532  2.401  2.253  2.166
3          Ghana  1.408  1.403  1.616  1.408  1.408  1.408  1.420  1.423
4        Lesotho  1.201  1.201  1.201  1.201  1.201  1.201  1.201  1.403
5      Mauritius  1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
6         Malawi  1.403  1.201  1.201  1.201  1.201  1.201  1.403  1.485
7        Namibia  1.413  1.403  1.403  1.403  1.201  1.201  1.201  1.201
8         Rwanda  1.650  1.604  1.604  2.143  2.132  2.345  2.369  2.022
9        Senegal  1.848  1.620  1.816  1.816  1.811  2.178  1.811  1.815
10  Sierra Leone  1.408  1.403  1.403  1.403  1.403  1.403  1.414  1.423
```

```
11      Tanzania  1.403  1.434  1.408  1.408  1.408  1.408  1.403  1.485
12  South Africa  1.403  1.805  1.805  1.805  1.805  1.805  1.805  1.906
13        Zambia  1.201  1.201  1.201  1.000  1.000  1.000  1.201  1.201

     2016   2017   2018   2019   2020   2021   2022   2023
0   1.403  1.403  1.610  1.615  1.413  1.621  1.608  1.639
1   1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.018
2   2.150  2.415  2.503  2.487  2.574  2.743  3.374  3.419
3   1.458  1.497  1.513  1.540  1.570  1.575  1.575  1.616
4   1.403  1.604  1.805  1.805  1.805  1.805  1.805  1.824
5   1.000  1.000  1.000  1.000  1.000  1.000  1.000  1.000
6   1.540  1.540  1.540  1.605  1.742  1.723  1.797  1.815
7   1.201  1.201  1.201  1.201  1.201  1.201  1.201  1.201
8   1.957  1.939  2.054  1.750  1.742  2.112  1.987  1.967
9   1.838  1.866  1.664  1.691  1.513  1.517  1.517  1.540
10  1.439  1.460  1.476  1.485  1.497  1.501  1.501  1.506
11  1.559  1.577  1.577  1.674  1.619  1.675  1.903  1.901
12  1.760  1.760  1.760  1.824  1.772  1.745  1.818  2.083
13  1.220  1.238  1.238  1.256  1.286  1.700  1.520  1.577
```

[23]:
```python
t = np.arange(2008, 2024)  # Time range

plt.figure(figsize=(12, 8))  # Adjust figure size for better visibility

# Define a list of line styles and markers to cycle through
line_styles = ['-', '--', '-.', ':']
markers = ['o', '^', 's', 'x', 'D', '+', '*']
colors = plt.cm.viridis(np.linspace(0, 1, len(GPI_SSA_1)))  # Use a colormap␣
↪for diverse colors

for i, (line_style, marker) in enumerate(zip(line_styles * len(markers), np.
↪tile(markers, len(line_styles)))):
    if i >= len(GPI_SSA_1):  # Check to prevent index error if more styles/
↪markers than countries
        break
    country = GPI_SSA_1['Country'][i]
    vals = list(GPI_SSA_1.iloc[i][1:])
    plt.plot(t, vals, marker=marker, linestyle=line_style, color=colors[i],␣
↪alpha=0.75, linewidth=2, label=country)

plt.title('Comparison of Peace Index by Country in SSA', fontsize=16)  # Title␣
↪with increased font size
plt.xlabel('Year', fontsize=14)  # X-axis label with increased font size
plt.ylabel('Index Value', fontsize=14)  # Y-axis label with increased font size
plt.legend(loc='best', ncol=2)  # Show legend with two columns to save space
plt.grid(True, which='both', linestyle='--', linewidth=0.5)  # Enhanced grid␣
↪visibility
```

```
plt.tight_layout()  # Adjust layout to fit everything
plt.show()
plt.savefig('GPI')
```




```
<Figure size 640x480 with 0 Axes>
```

[24]:
```
GPI_SSA_stats = GPI_SSA_1.set_index('Country').transpose().describe()
GPI_SSA_stats = GPI_SSA_stats.loc['std'].sort_values()
```

[25]:
```
selection = list(GPI_SSA_stats.index[:-1])
print(selection)
```

```
['Mauritius', 'Botswana', 'Sierra Leone', 'Ghana', 'Namibia', 'Angola', 'South
Africa', 'Tanzania', 'Senegal', 'Zambia', 'Malawi', 'Rwanda', 'Lesotho']
```

[ ]:
```

```

B Financial Model

Stochastic

March 14, 2024

[1]:
```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.integrate import cumtrapz
%matplotlib inline
```

```
Intel MKL WARNING: Support of Intel(R) Streaming SIMD Extensions 4.2 (Intel(R)
SSE4.2) enabled only processors has been deprecated. Intel oneAPI Math Kernel
Library 2025.0 will require Intel(R) Advanced Vector Extensions (Intel(R) AVX)
instructions.
Intel MKL WARNING: Support of Intel(R) Streaming SIMD Extensions 4.2 (Intel(R)
SSE4.2) enabled only processors has been deprecated. Intel oneAPI Math Kernel
Library 2025.0 will require Intel(R) Advanced Vector Extensions (Intel(R) AVX)
instructions.
```

1 Case Study, Assumptions, Data

As an example of an energy-intensive business, we consider an arbitrary hotel in Tanzania.

Average hotel consumption in the US is 50-60 kWh. Due to lower occupancies, simpler designs and less amenities, let's consider 20-30 kWh per year.

[2]:
```
A_base_consumption = 25000 # yearly base consumption of energy [kWh]
```

1.0.1 Economic Variables

Notable exceptions are African countries and Mexico. For Africa, we use an average WACC of approximately 12% for the whole continent

[3]:
```
WACC = 0.12 # Annual discount rate
```

[4]:
```
inflation = 1.045 # annual inflation for Tanzania
```

1.0.2 Energy Variables

Diesel Costs We aim to obtain a base diesel price in dollars per kWh.

$Price/kWh = \frac{Price\ per\ Litre}{Specific\ Energy} \times \frac{1}{Engine\ Efficiency} \times \frac{1}{0.278}$

[5]:
```
diesel_base_perL = 1.32 # base cost of diesel [$/L] (https://www.theeastafrican.
 ↪co.ke/tea/business/
 ↪more-pain-at-the-pump-as-fuel-prices-rise-to-new-levels-in-tanzania-4359956#)
specific_E = 38 # [MJ] - may be lower for poorer quality diesel
efficiency = 0.3 # for diesel engines at shaft - reduces if generator not␣
 ↪serviced
c = 0.278 # conversion from MJ to kWh
diesel_base = (diesel_base_perL/specific_E) * (1/efficiency) * (1/c) # base␣
 ↪cost of diesel [$/kWh]
print(diesel_base)
```

```
0.41650889814464215
```

Annual diesel inflation - inflation Rate at 3.7%

[6]:
```
A_diesel_inflation = 1.035
```

Diesel Emissions

[7]:
```
# Emissions data (in kilograms or grams per litre)
CO2_emission = 2.68  # Carbon Dioxide (CO2) in kilograms per litre of diesel␣
 ↪burned
NOx_emission_min = 6/1000  # Minimum Nitrogen Oxides (NOx) emission in kg per␣
 ↪litre
NOx_emission_max = 15/1000  # Maximum Nitrogen Oxides (NOx) emission in kg per␣
 ↪litre
PM_emission = 0.1/1000  # Particulate Matter (PM) in kg per litre
HC_emission = 0.6/1000  # Hydrocarbons (HC) in kg per litre
CO_emission = 0.3/1000  # Carbon Monoxide (CO) in kg per litre
```

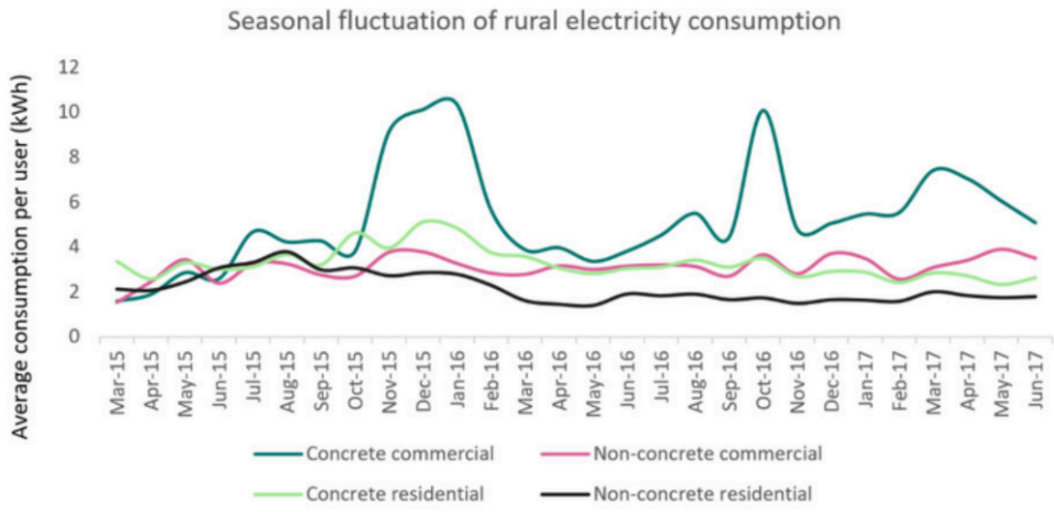
[8]:
```
def DieselEmissions_per_kWh(MassPerLitre):
    specific_E = 38 # [MJ] - may be lower for poorer quality diesel
    efficiency = 0.3 # for diesel engines at shaft - reduces if generator not␣
 ↪serviced
    c = 0.278 # conversion from MJ to kWh
    return (MassPerLitre/specific_E) * (1/efficiency) * (1/c) # emissions from␣
 ↪diesel [kg/kWh]
```

[9]:
```
CO2_emission_per_kWh = DieselEmissions_per_kWh(CO2_emission)
NOx_emission_min_per_kWh = DieselEmissions_per_kWh(NOx_emission_min)
NOx_emission_max_per_kWh = DieselEmissions_per_kWh(NOx_emission_max)
PM_emission_per_kWh = DieselEmissions_per_kWh(PM_emission)
HC_emission_per_kWh = DieselEmissions_per_kWh(HC_emission)
CO_emission_per_kWh = DieselEmissions_per_kWh(CO_emission)
```

Electricity Costs Using average commercial rate for June 2023

```
[10]: electricity_base = 0.094 # base cost of electricity [$/kWh]
```

Commercial electicity consumption tends to spike during winter months (hotter period, requiring more cooling and higher tourist flow):



Yearly electricity inflation (between 2017 and 2023)

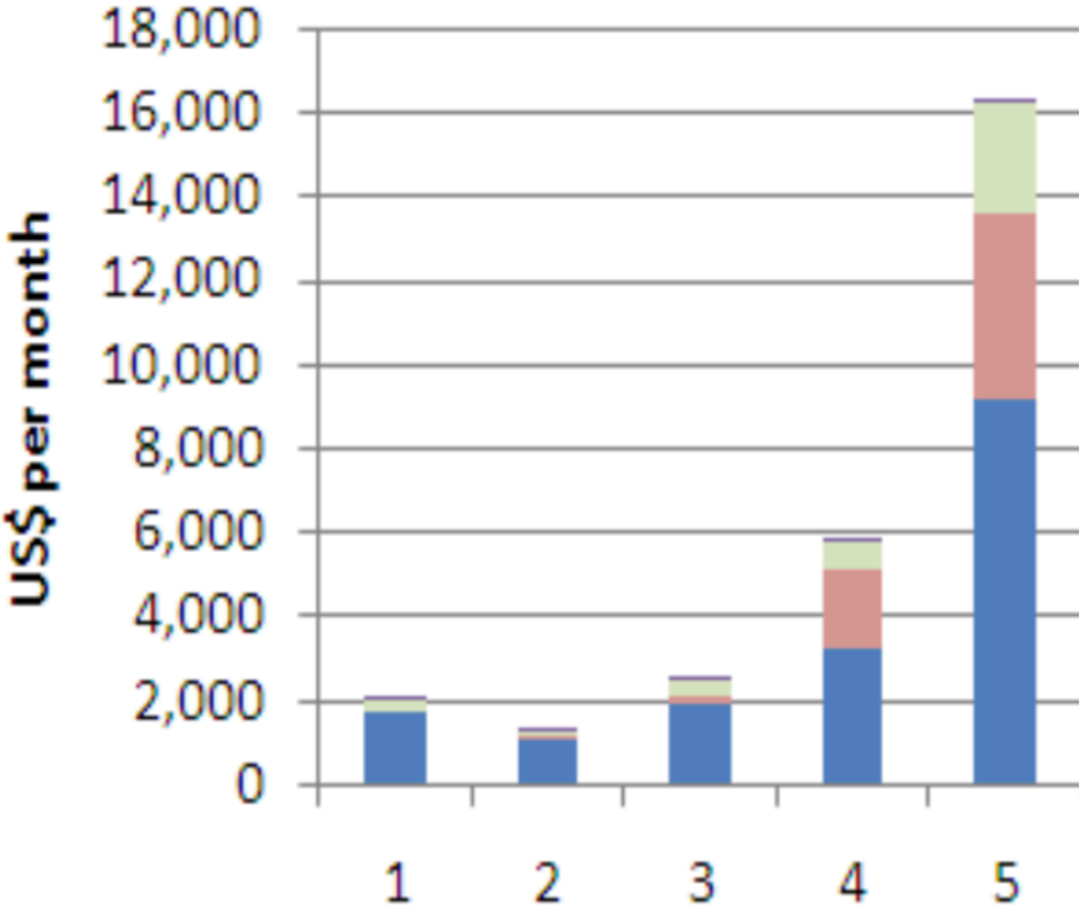
```
[11]: A_electricity_inflation =  (0.094/0.0816)**(1/4)
```

Generators For 10kVa (commercial use) Generators, the price range is 3,900,000 - 7,100,000 10kVa converts to 8kW

```
[12]: usd_rate = 0.0004
generator_purchase = usd_rate*(3900000 + 7100000)/2 # purchase cost of␣
 ↪generator [$]
```

```
[13]: generator_purchase
```

```
[13]: 2200.0
```



Generator Maintenance Cost Take mean spend on maintenace to be 6k/5 = 1.2k

[14]:
```
M_generator_maintenance = 1200 # yearly generator maintenance cost
```

Generator Efficiency Loss and Liftetime

[15]:
```
A_generator_loss = 0.02 # yearly efficiency loss of generator
lifetime_generator = 15 # years
```

Power Packs

[16]:
```
newPowerPack_purchase = 1000 # purchase cost of single new module [$]
newPowerPack_capacity = 6.5 # capacity of new module [kWh]
soh = 0.8 # 80% state of health for a used module
discount = 0.5 # Assume discont for a used module
usedPowerPack_capacity = soh*newPowerPack_capacity # Used module capacity
usedPowerPack_purchase = newPowerPack_purchase*(1-discount) # Used module price
```

Power Pack Maintenance Power pack maintenance is less intense, so assume 50% of generator cost

```
[17]: M_powerPack_maintenance = M_generator_maintenance/2 # yearly power pack␣
    ↪maintenance cost
```

Power Pack Efficiency Loss

```
[18]: A_powerPack_loss = 0.2 # yearly efficiency loss of power pack
```

Type of Solar Panel	Average Cost per m2
Monocrystalline	£250 – £350
Polycrystalline	£200 – £300
Thin-Film	£150 – £200

Solar Panels https://www.solarguide.co.uk/how-much-does-it-cost-to-install-solar-panels#:~:text=Average%20Cost%20per%20m2&text=These%20approximate%20prices%20depend%20on,poly%2

```
[19]: kWh_per_m_day = 1
price_per_m = 200
N_cells = 10
maintenance_pa = 0.05
```

2 Modelling

2.1 Power Cuts

```
[20]: def yearlyPowerCuts(years, power_cuts_per_month, avg_duration_hours,␣
    ↪std_deviation_hours):
        # Initialize an array for the entire year
        # Column 1: Day of the year, Column 2: Duration of power cut
        yearly_power_cuts = np.zeros((365*years, 2), dtype=int)
        yearly_power_cuts[:, 0] = np.arange(1, 365*years + 1)

        for month in range(12*years):
            # Calculate the start and end day of the month
            start_day = month * (365 // 12)
            end_day = (month + 1) * (365 // 12)

            # Generate random days for power cuts within the month
            power_cut_days = random.sample(range(start_day, end_day),␣
    ↪power_cuts_per_month)

            # Generate random durations for each power cut
            power_cut_durations = np.random.normal(avg_duration_hours,␣
    ↪std_deviation_hours, power_cuts_per_month)
            power_cut_durations = np.round(power_cut_durations).astype(int)
```

```
        power_cut_durations = np.clip(power_cut_durations, 1, None)  # Ensure␣
↪durations are at least 1 hour

        # Update the yearly array
        for day, duration in zip(power_cut_days, power_cut_durations):
            yearly_power_cuts[day, 1] = duration

    return yearly_power_cuts
```

2.2 Service Days

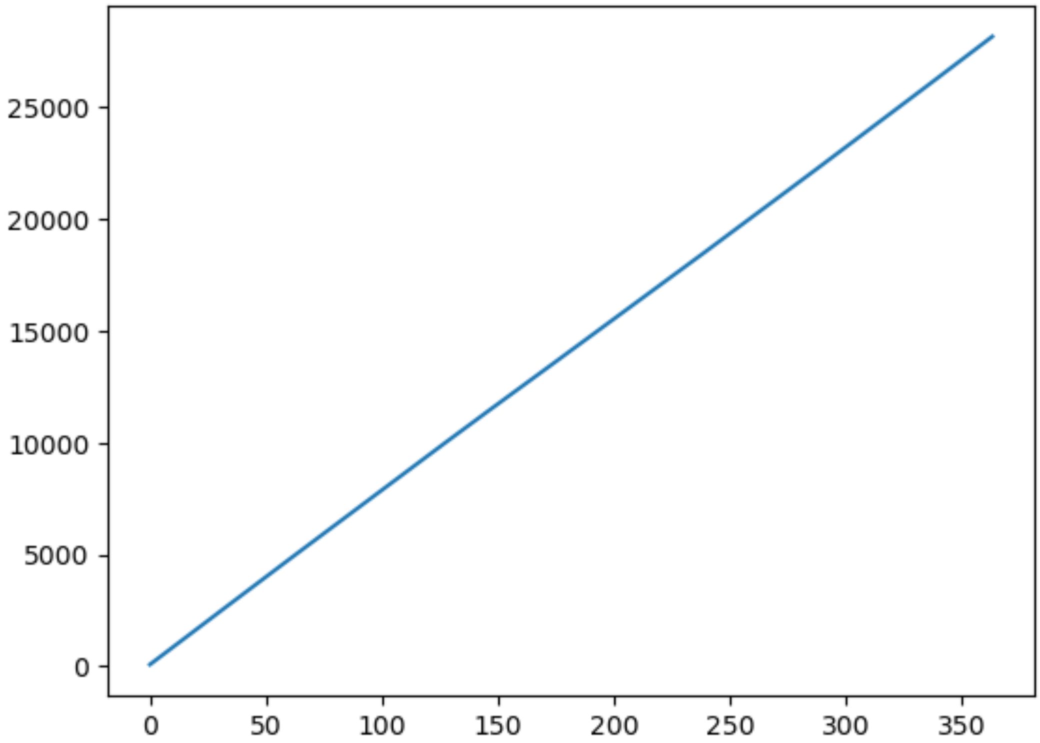
[21]:
```
def serviceDays(years, start_value, days_sd, spacing_mean):

    max_value = 366*years  # Cap value, assuming a year limit
    num_elements = 12*years  # Number of elements

    # Initialize the array
    service_days = np.zeros(num_elements, dtype=int)
    service_days[0] = start_value

    # Generate the rest of the elements with random spacing
    for i in range(1, num_elements):
        spacing = int(np.round(np.random.normal(spacing_mean, days_sd)))
        next_value = service_days[i - 1] + spacing

        # Applying the cap
        if next_value > max_value:
            service_days[i] = max_value
            # Stop adding more days once the cap is reached
            break
        else:
            service_days[i] = next_value

    # Trimming the array to remove any trailing zeros if the cap was reached␣
↪before filling all elements
    return service_days[service_days != 0]
```

2.3 Electricity Consumption

[22]:
```
def Consumption(years, kWh_per_year):    # Returns daily consumption

    days = years*365
    kWh_per_year = np.random.normal(kWh_per_year, 0.01*kWh_per_year)
    KWh_per_m_day =  kWh_per_year/365
    sd = KWh_per_m_day*0.001
```

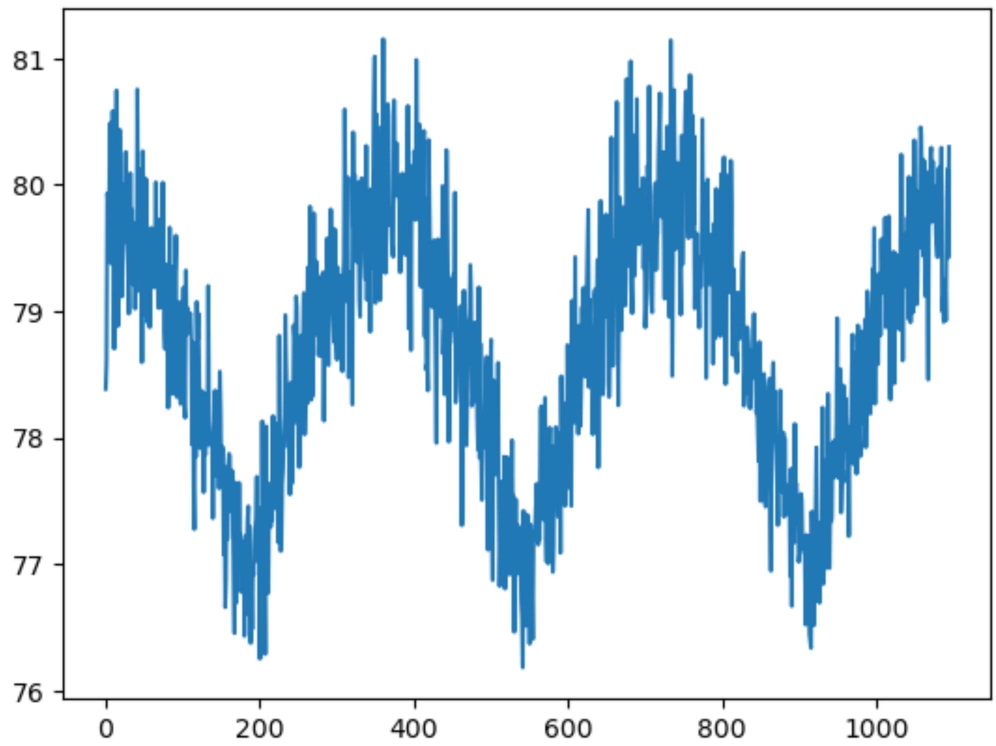
```
    data = np.array([ ])

    for day in np.arange(days):

        # Decreasing the amplitude of the coefficients for smoother fluctuations
        coeffs = np.random.normal(0.1, 0.005)   # Reduced mean and standard␣
 ↪deviation
        correction = (coeffs * (3 + np.abs(np.cos(day * (np.pi / 365)))))/3

        shift = ((KWh_per_m_day * correction).sum() - kWh_per_year)
        KWh_per_m_day = KWh_per_m_day * correction - shift / 365

        data = np.append(data,KWh_per_m_day)

    return data

plt.plot( cumtrapz(Consumption(1, 25000)))
print(cumtrapz(Consumption(1, 25000))[-1])
```

```
28396.40479760173
```



[23]:
```
plt.plot( (Consumption(3, 25000)))
```

[23]: [<matplotlib.lines.Line2D at 0x7fc3b029ec40>]



2.4 Inflation

[24]:
```
def Inflation(annual_inflation, years, sd):

    days=365*years
    # Daily rate from annual rate
    daily_rate = (annual_inflation ** (1/days))-1

    # Generating daily values with random fluctuations
    daily_values = []
    for _ in range(days):
        # Apply random fluctuation
        fluctuated_rate = daily_rate * (1 + np.random.uniform(-sd, sd))
        daily_values.append(1 + fluctuated_rate)

    return np.array(daily_values)
```

[ ]:
```

```

2.5 Applying Variable Models to Generate Data

[25]:
```
def DataModel(years, M_generator_maintenance, M_powerPack_maintenance,␣
↪A_diesel_inflation, diesel_base, A_electricity_inflation, electricity_base,␣
↪A_generator_loss):

    #Power Cuts
    data = yearlyPowerCuts(years,power_cuts_per_month, avg_duration_hours,␣
↪std_deviation_hours)

    cuts = data[:,1]
    days = data[:,0]

    # Service days
    service_days = serviceDays(years, start_value, days_sd, spacing_mean)

    #Consumption
    consumption = Consumption(years, KWh_per_year)

    #Inflation
    inflation = Inflation(annual_inflation, years, halfrange)

    #Generator Service Prices (Inflated)
    generator_service_prices = [M_generator_maintenance]

    for i in range(len(inflation)-1):
        k = inflation[i]
        p = generator_service_prices[i-1]*k
        generator_service_prices.append(p*k)

    generator_service_prices = np.array(generator_service_prices)


    #Generator efficiency
    N_days = years*365
    eff = np.ones(N_days)
    k_day = (1-A_generator_loss)**(1/N_days)
    for i in range(len(eff)):
        if i != 0:
            eff[i] = eff[i-1]*k_day

    #Power Pack Service Prices (Inflated)
    PowerPack_service_prices = [M_powerPack_maintenance]

    for i in range(len(inflation)-1):
        k = inflation[i]
        p = PowerPack_service_prices[i-1]*k
```

```
        PowerPack_service_prices.append(p*k)

    PowerPack_service_prices = np.array(PowerPack_service_prices)


    #Diesel Inflation
    diesel_inflation = Inflation(A_diesel_inflation, years,␣
↪halfrange_diesel_inflation)

    #Diesel Prices [$/kWh] (Inflated)
    diesel_prices = [diesel_base]

    for i in range(len(diesel_inflation)-1):
        k = diesel_inflation[i]
        p = diesel_prices[i-1]*k
        diesel_prices.append(p*k)

    diesel_prices = np.array(diesel_prices)

    #Electricity Inflation
    electricity_inflation = Inflation(A_electricity_inflation, years,␣
↪halfrange_elec_inflation)

    #Electricity Prices [$/kWh] (Inflated)
    electricity_prices = [electricity_base]

    for i in range(len(electricity_inflation)-1):
        k = electricity_inflation[i]
        p = electricity_prices[i-1]*k
        electricity_prices.append(p*k)

    electricity_prices = np.array(electricity_prices)

    return cuts, days, service_days, consumption, generator_service_prices,␣
↪PowerPack_service_prices, diesel_prices, electricity_prices, eff
```

[26]:
```
# We Assume January Start
years = 3

# Power cuts
power_cuts_per_month = 9
avg_duration_hours = 6
std_deviation_hours = 2

# Service days
start_value = 30
days_sd = 5
```

```
spacing_mean = 30

#Consumption
KWh_per_year = 25000

#Inflation
halfrange = 0.1
annual_inflation = 1.045

#Generator
# M_generator_maintenance - defined above

# M_powerPack_maintenance - defined above

#Diesel Inflation
halfrange_diesel_inflation = 0.1
# A_diesel_inflation - defined above
# diesel_base - defined above

#Electricity Inflation
halfrange_elec_inflation = 0.1
# A_electricity_inflation - defined above
# electricitybase - defined above

cuts, days, service_days, consumption, generator_service_prices,␣
↪PowerPack_service_prices, diesel_prices, electricity_prices, eff =␣
↪DataModel(years, M_generator_maintenance, M_powerPack_maintenance,␣
↪A_diesel_inflation, diesel_base, A_electricity_inflation, electricity_base,␣
↪A_generator_loss)
```

2.6 Modelling Generator Costs

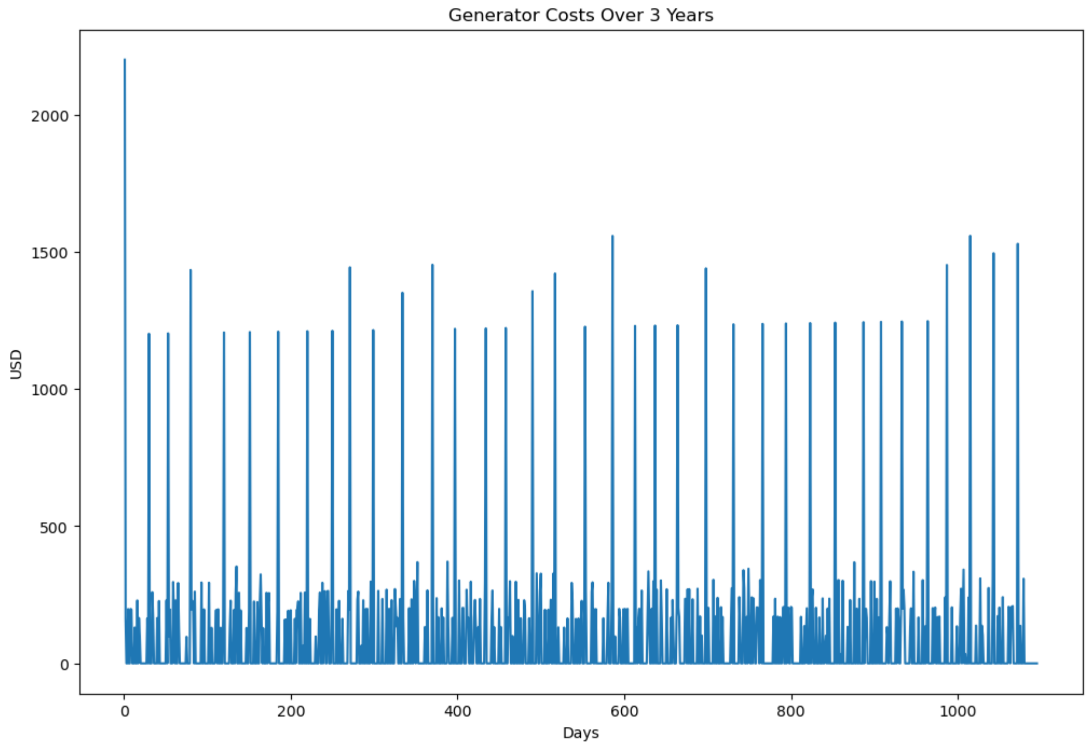
[ ]:

```
```

[28]:

```
# For the generator
generator_costs = np.array([])

# Start the time
for day in days:

    day_spend = 0

    # Accounting for lifetime
    if (day-1)%(lifetime_generator*365)==0:
        day_spend += generator_purchase

    if day in service_days:
```

```
        service_cost = generator_service_prices[day]
        day_spend += service_cost


    # Cut
    efficiency = eff[day-2]
    duration = cuts[day-1]
    price = diesel_prices[day-1]
    cut_cost_per_kWh = duration*price
    kWh_used = consumption[day-1]
    cut_cost = cut_cost_per_kWh*kWh_used/efficiency
    day_spend += cut_cost

    generator_costs = np.append(generator_costs,day_spend)

plt.figure(figsize=(12,8))
plt.title(f'Generator Costs Over {years} Years')
plt.xlabel('Days')
plt.ylabel('USD')
plt.plot(days, generator_costs)
plt.savefig(f'Generator Costs Over {years} Years')
```



2.7 Modelling Power Pack Costs

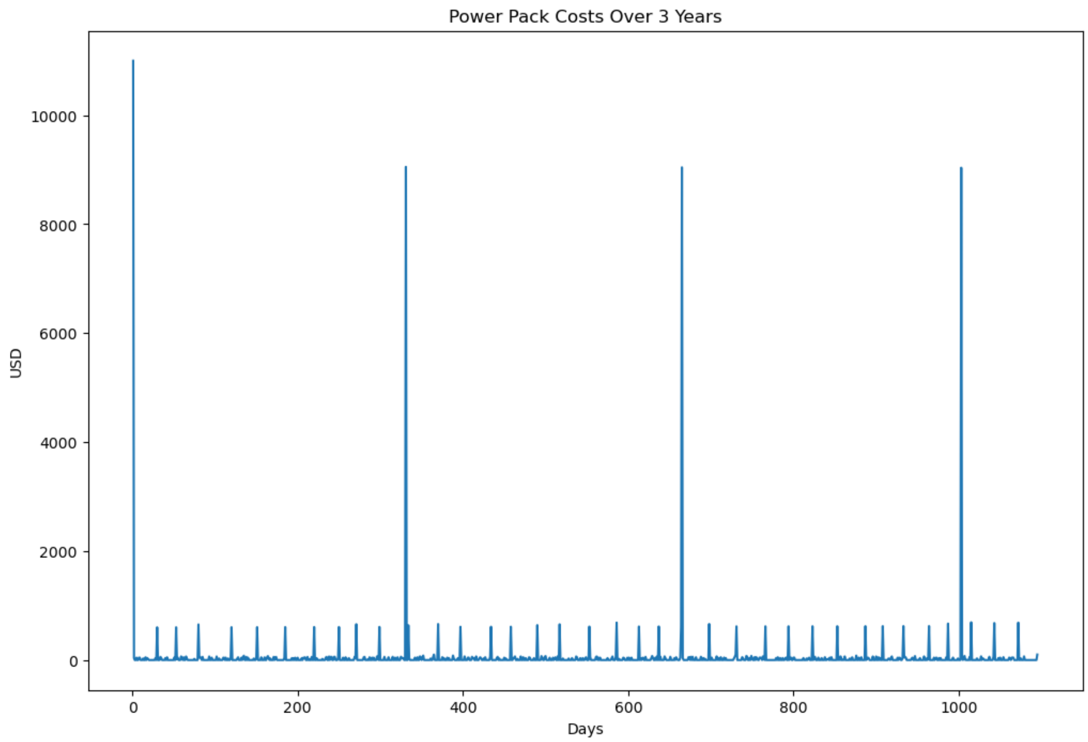
Assume Power pack is functional for 100 more cycles, until it is at risk of failing.

[ ]:
```
usedPowerPack_capacity
```

[38]:
```
# For the Power Pack
PowerPack_costs = np.array([])

cycle = 0
cycle_limit = 100
N_packs = 18


day_spend = usedPowerPack_purchase*N_packs

initial_solar_investment = price_per_m * N_cells

day_spend += initial_solar_investment

# Start the time
for day in days:


    # Cut
    duration = cuts[day-1] # duration of power cut (zero if none)

    if duration != 0:
        cycle +=1

    # Accounting for lifetime
    if cycle == cycle_limit:
        day_spend += usedPowerPack_purchase*N_packs
        cycle = 0

    # Add maintenance costs each year
    if day%365==0:
        PV_service = initial_solar_investment*maintenance_pa
        print(PV_service)
        day_spend += PV_service

    # Charge
    price = electricity_prices[day-1]
    cut_cost_per_kWh = duration*price
    kWh_used = consumption[day-1]
    electro_spend = kWh_used*cut_cost_per_kWh

    # Discount for how much of it is solar
```

```
    solar_generated = kWh_per_m_day * N_cells
    solar_discount = solar_generated * electricity_prices[day-1]

    # Account for solar surplus
    if solar_discount > electro_spend:
        electro_spend = 0
    else:
        electro_spend -= solar_discount


    if day in service_days:
        service_cost = PowerPack_service_prices[day]
        day_spend += service_cost

    day_spend += electro_spend

    PowerPack_costs = np.append(PowerPack_costs,day_spend)

    day_spend = 0

plt.figure(figsize=(12,8))
plt.title(f'Power Pack Costs Over {years} Years')
plt.xlabel('Days')
plt.ylabel('USD')
plt.plot(days, PowerPack_costs)
plt.savefig(f'Power Pack Costs Over {years} Years')
```

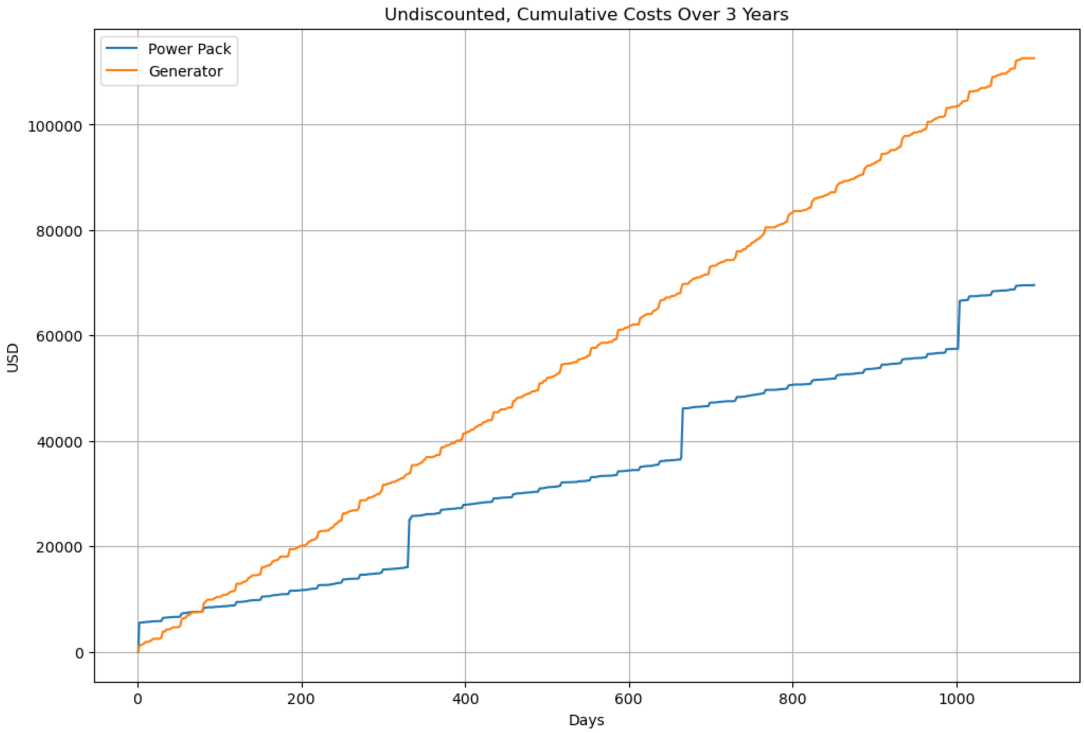
```
100.0
100.0
100.0
```




```
[ ]:
```

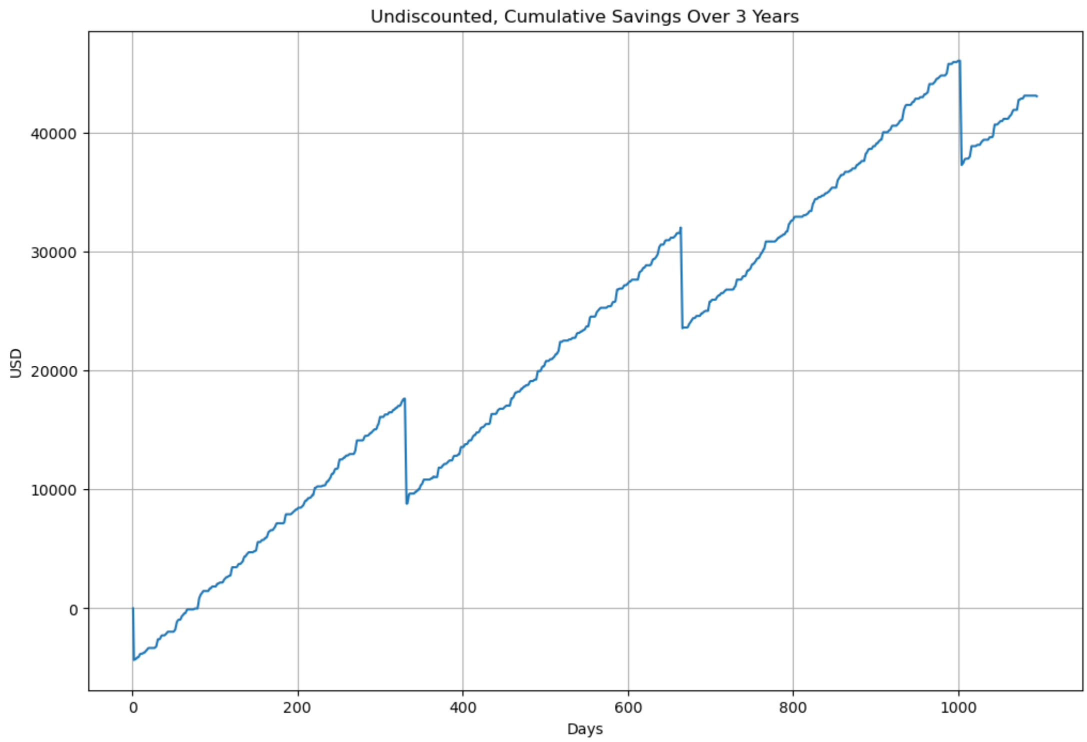
2.8 Comparison

```
[39]: PowerPack_costs_cumulative = np.append(0,cumtrapz(PowerPack_costs, days))
generator_costs_cumulative = np.append(0,cumtrapz(generator_costs, days))

plt.figure(figsize=(12,8))
plt.plot(days, PowerPack_costs_cumulative, label = 'Power Pack')
plt.plot(days, generator_costs_cumulative, label = 'Generator')

plt.title(f'Undiscounted, Cumulative Costs Over {years} Years')
plt.xlabel('Days')
plt.ylabel('USD')
plt.legend()
plt.grid()
plt.savefig(f'Undiscounted, Cumulative Costs Over {years} Years')
```



2.8.1 Savings

[40]:
```
Savings = generator_costs_cumulative - PowerPack_costs_cumulative
plt.figure(figsize=(12,8))
plt.plot(days, Savings)

plt.title(f'Undiscounted, Cumulative Savings Over {years} Years')
plt.xlabel('Days')
plt.ylabel('USD')
plt.grid()
plt.savefig(f'Undiscounted, Cumulative Savings Over {years} Years')
```



[ ]:

```

```

[ ]:

```
# 1 solar PV cell

kWh_per_metre = 1
```

2.8.2 NPV

[ ]:

```
def NPV(WACC, Values):
    k_day = (1+WACC)**(1/365)

    NPV = []

    for i in range(len(Savings)):
        if i == 0:
            s = Savings[i]
            NPV.append(s)
        else:
            s = Savings[i-1]
            discounted = s/( k_day**(i) )
            NPV.append(discounted)

    NPV = np.array(NPV)
```

```
    return NPV

plt.figure(figsize=(15, 10))
NPV = NPV(WACC, Savings)
plt.plot(NPV)
plt.title(f'Savings, {WACC*100}% Annual Discount Rate', fontsize=26)  #␣
 ↪Increase font size for the title
plt.ylabel('USD Saved', fontsize=24)  # Increase font size for the ylabel
plt.xlabel('Years', fontsize=24)  # Increase font size for the xlabel
plt.xticks([0, 365, 2 * 365, 3 * 365], ['Year 0', 'Year 1', 'Year 2', 'Year␣
 ↪3'], fontsize=24)  # Increase font size for xticks
plt.grid(which='both', color='gray', linestyle='--', linewidth=0.4)
plt.savefig('Savings', dpi=300)  # Save the plot with higher resolution (300␣
 ↪DPI)
plt.show()
```

[ ]:
```
def generatorEmissions(emission):
    # For the generator
    generator_emissions = np.array([])

    # Start the time
    for day in days:

        day_emission = 0  # Initialize daily emissions

        # Cut
        efficiency = eff[day-1]  # Note: eff[day-1] instead of eff[day-2]
        duration = cuts[day-1]

        cut_emission_per_kWh = duration * emission
        kWh_used = consumption[day-1]
        cut_emission = cut_emission_per_kWh * kWh_used / efficiency
        day_emission += cut_emission

        # Accumulate daily emissions
        generator_emissions = np.append(generator_emissions, day_emission)

    return generator_emissions
```

[ ]:
```
CO2_emission_per_kWh = DieselEmissions_per_kWh(CO2_emission)
NOx_emission_per_kWh = DieselEmissions_per_kWh(NOx_emission_max)
PM_emission_per_kWh = DieselEmissions_per_kWh(PM_emission)
HC_emission_per_kWh = DieselEmissions_per_kWh(HC_emission)
CO_emission_per_kWh = DieselEmissions_per_kWh(CO_emission)


pollutants = ["CO2", "NOx", "PM", "HC", "CO"]
```

```python
emissions_list = [CO2_emission_per_kWh, NOx_emission_per_kWh, PM_emission_per_kWh, HC_emission_per_kWh, CO_emission_per_kWh]

# Specify colors for each pollutant
colors = ["blue", "green", "red", "purple", "orange"]

# Create a dictionary to store emissions results for each pollutant
emissions_results = {}

# Calculate and store daily emissions for each pollutant
for pollutant, emission_value, color in zip(pollutants, emissions_list, colors):
    emissions_results[pollutant] = generatorEmissions(emission_value)
    emissions_results[pollutant + "_color"] = color

# Increase font size for all text elements on the plots
plt.rcParams.update({'font.size': 20})

# Create cumulative graphs for each pollutant using cumtrapz
num_rows = 2  # Number of rows in the matrix
num_cols = 3  # Number of columns in the matrix
fig, axs = plt.subplots(num_rows, num_cols, figsize=(18, 12))

# Flatten the axs array to make it easier to index
axs = axs.ravel()

for i, pollutant in enumerate(pollutants):
    daily_emissions = emissions_results[pollutant]
    cumulative_emissions = cumtrapz(daily_emissions, initial=0)
    color = emissions_results[pollutant + "_color"]
    axs[i].plot(days, cumulative_emissions, label=f"Cumulative {pollutant}", color=color)
    axs[i].set_xlabel("Day")
    axs[i].set_ylabel(f"Cumulative {pollutant} Emissions (kg)")
    axs[i].set_title(f"Cumulative {pollutant} Emissions")
    axs[i].legend()
    axs[i].grid(True)

# Hide any empty subplots
for i in range(len(pollutants), num_rows * num_cols):
    fig.delaxes(axs[i])

# Save the matrix of graphs as a single image
plt.tight_layout()
plt.savefig("Emissions.png", dpi=300)  # Save as "Emissions.png" with 300 DPI resolution
plt.show()
```

```
[ ]:
```

```
[ ]:
```