Climate Change Prevention/Mitigation

TEAM 2

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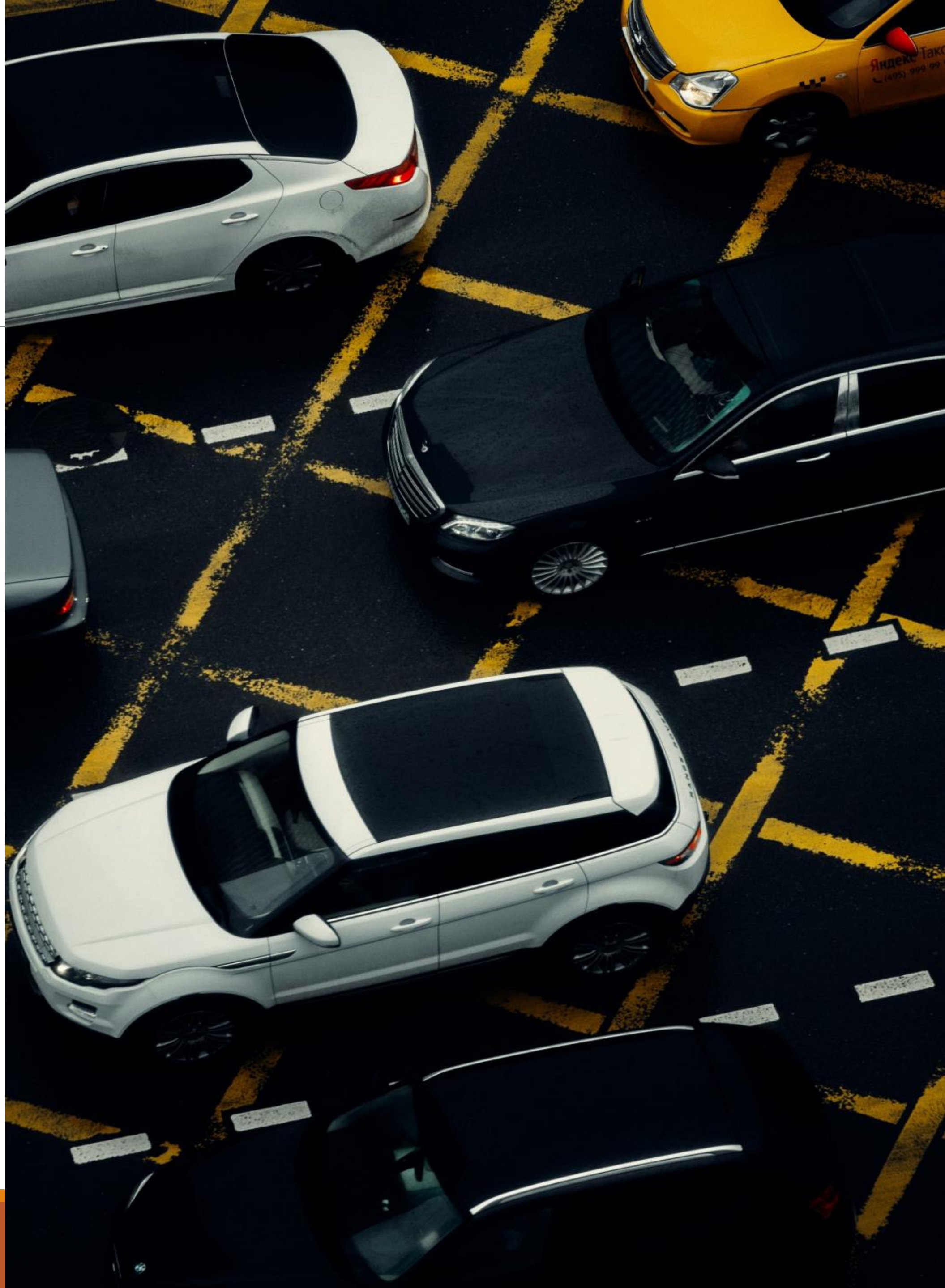
Project Overview

Background:

Climate change is a global issue characterized by changes in temperature, precipitation patterns, sea levels, and increasing frequencies of extreme weather conditions. This project focuses on mitigating the adverse effects of climate change with a specific focus on reducing carbon dioxide (CO_2) emissions, which are a major contributor to global warming.

Objective: The project will utilize a combination of qualitative and quantitative research methods including data collection, statistical analysis, and quality management tools to propose and validate solutions.



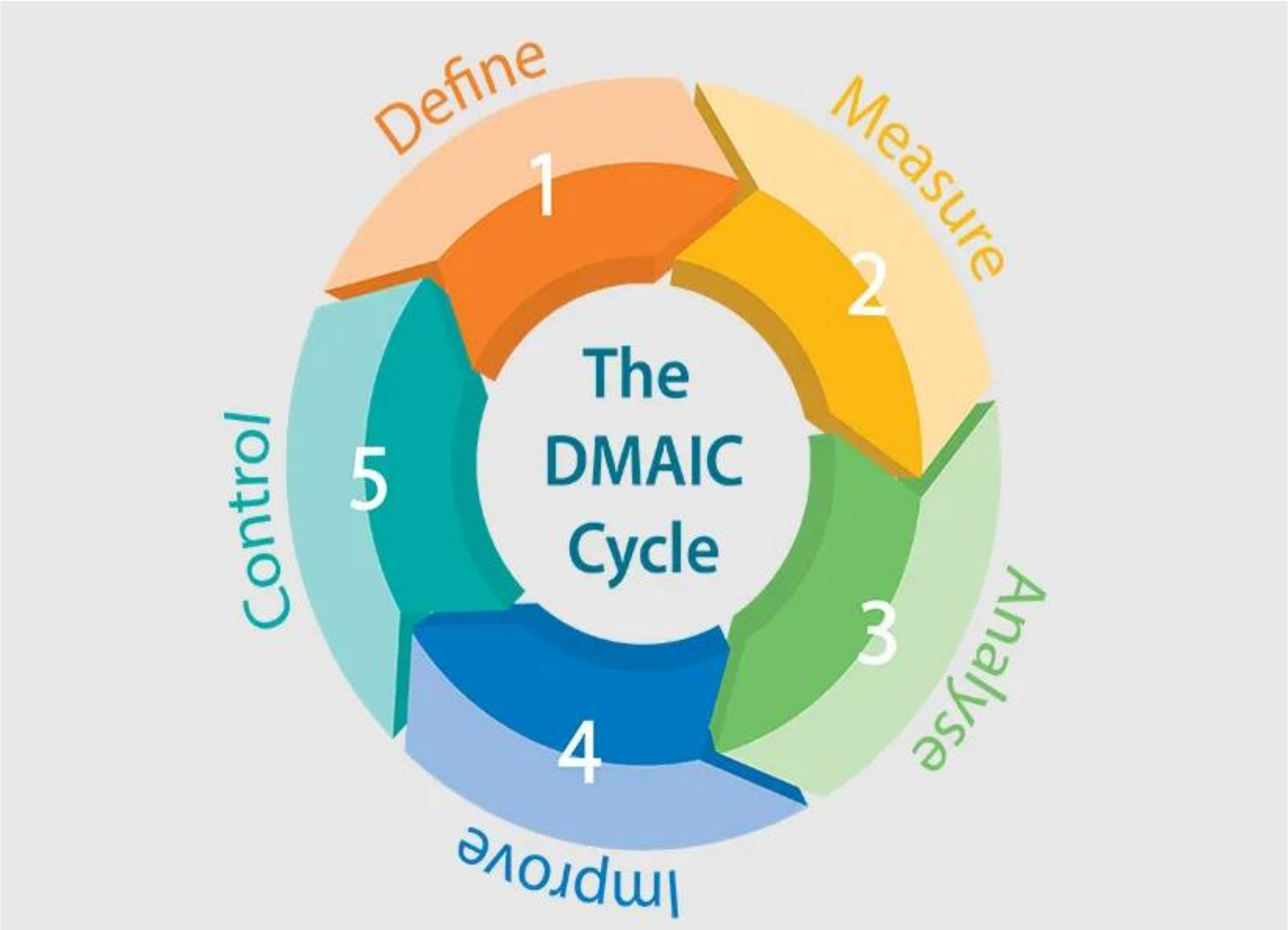
COPC

Total Estimated Annual COPQ: $1.43 billion

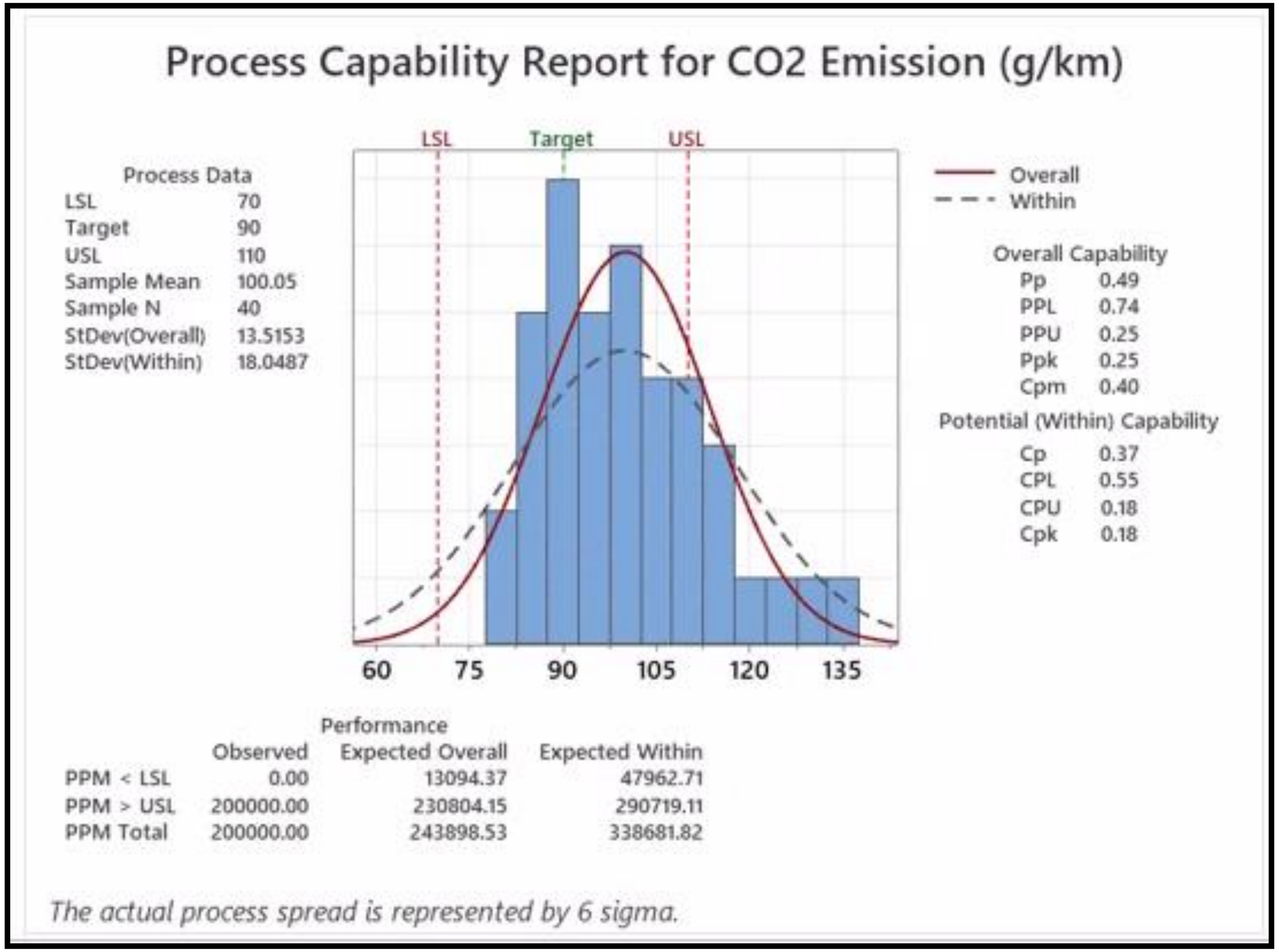
Cost Category	Description	Estimated Annual Cost	Data Assumptions
Direct Costs			
Healthcare Expenditures	Costs of treating respiratory and cardiovascular diseases linked to poor air quality.	$600 million	3% of the urban population affected annually, average treatment cost $2,000
Environmental Restoration	Costs for cleaning waterways, air quality improvement projects, and reforestation due to environmental damage.	$250 million	500 projects per year, average cost $500,000 per project
Indirect Costs			
Lost Productivity	Productivity losses due to increased illness and reduced work capacity from poor air quality.	$400 million	5% reduction in productivity for 3% of the workforce
Absenteeism	Costs related to employees missing work due to health issues caused by pollution.	$180 million	3% of the workforce, average cost $1,200 per employee
Intangible Costs			
Quality of Life	Decreased quality of life and well-being due to environmental degradation.	Not monetarily quantifiable	Difficult to quantify but significantly impacts public health and social stability
Biodiversity Loss	Costs associated with the loss of biodiversity, which can affect ecosystem stability and services.	Not monetarily quantifiable	Loss of approximately 1% of local species annually

Design

Problem Statement: In the metropolitan area of City X, vehicle emissions are currently contributing 40% of the total CO_2 emissions, which is significantly above the national average. Data indicates that on average, CO_2 emissions from vehicles amount to 150 grams per kilometer, exceeding the target limit of 110 grams per kilometer set by environmental regulations. The goal is to reduce these emissions by 30%, bringing them below the national average and within regulatory limits.



Process Capability Analysis



The CO2 Emission in the City were Measured and analyzed before and after the process improvement.

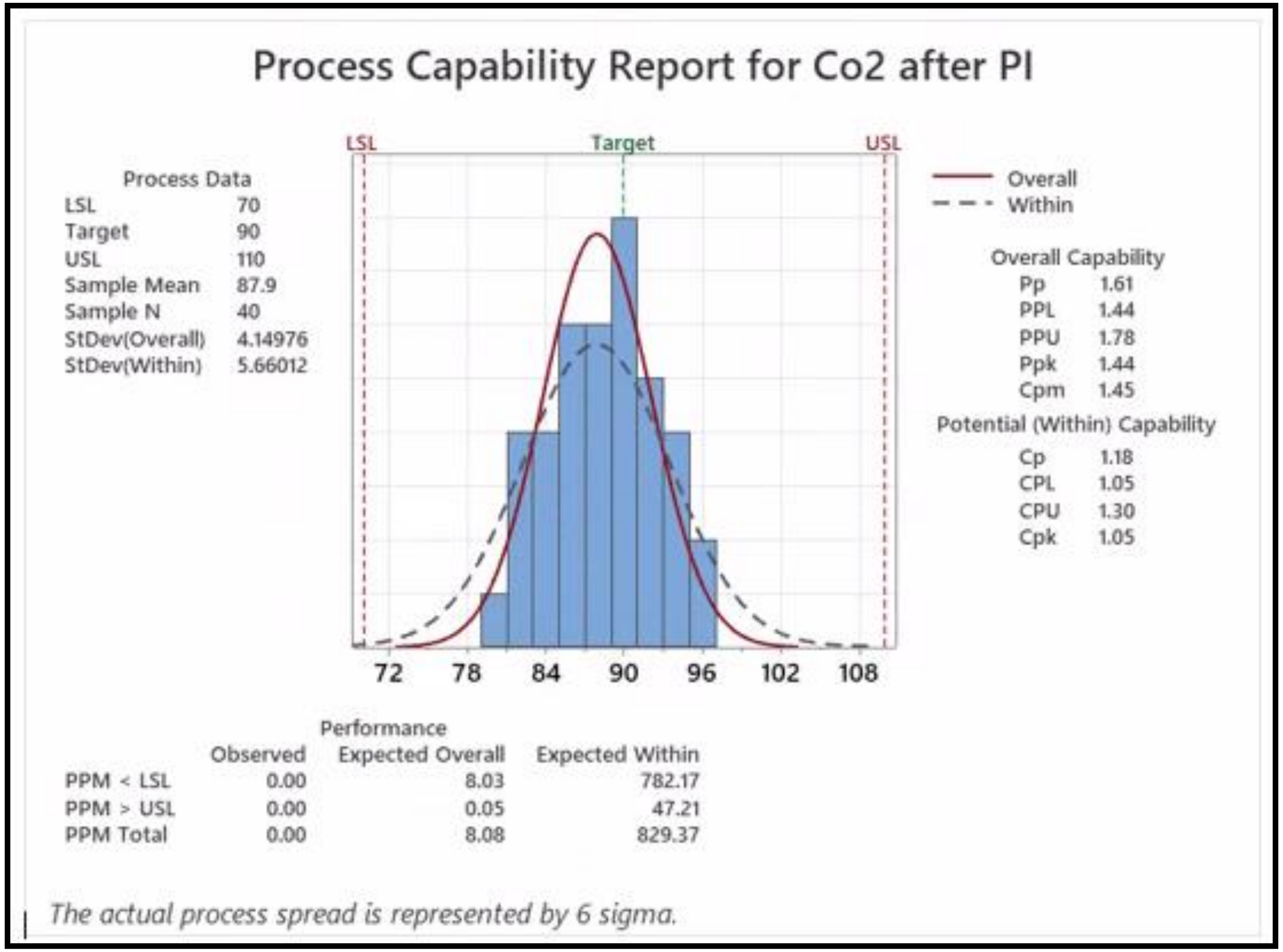
USL (Upper Specification Limit): 110 g/km (this is the regulatory target limit for CO2 emissions).
LSL (Lower Specification Limit): 70 g/km (this might be an aspirational target for eco-friendly vehicles).
Target: 90 g/km (average desired performance).

The Cp value is 0.37, which is far below the benchmark of 1.33, suggesting that the process spread is much wider than the specification limits, indicating a non-capable process.

The Cpk value is also 0.18, reinforcing the finding that the process is not capable of meeting the specification limits consistently when considering the process centering.

The PPM > USL is significantly high at 2,000,000, suggesting that a large number of units exceed the Upper Specification Limit

Process Capability Analysis (After PI)



Process Improvement: Traffic Flow Optimization

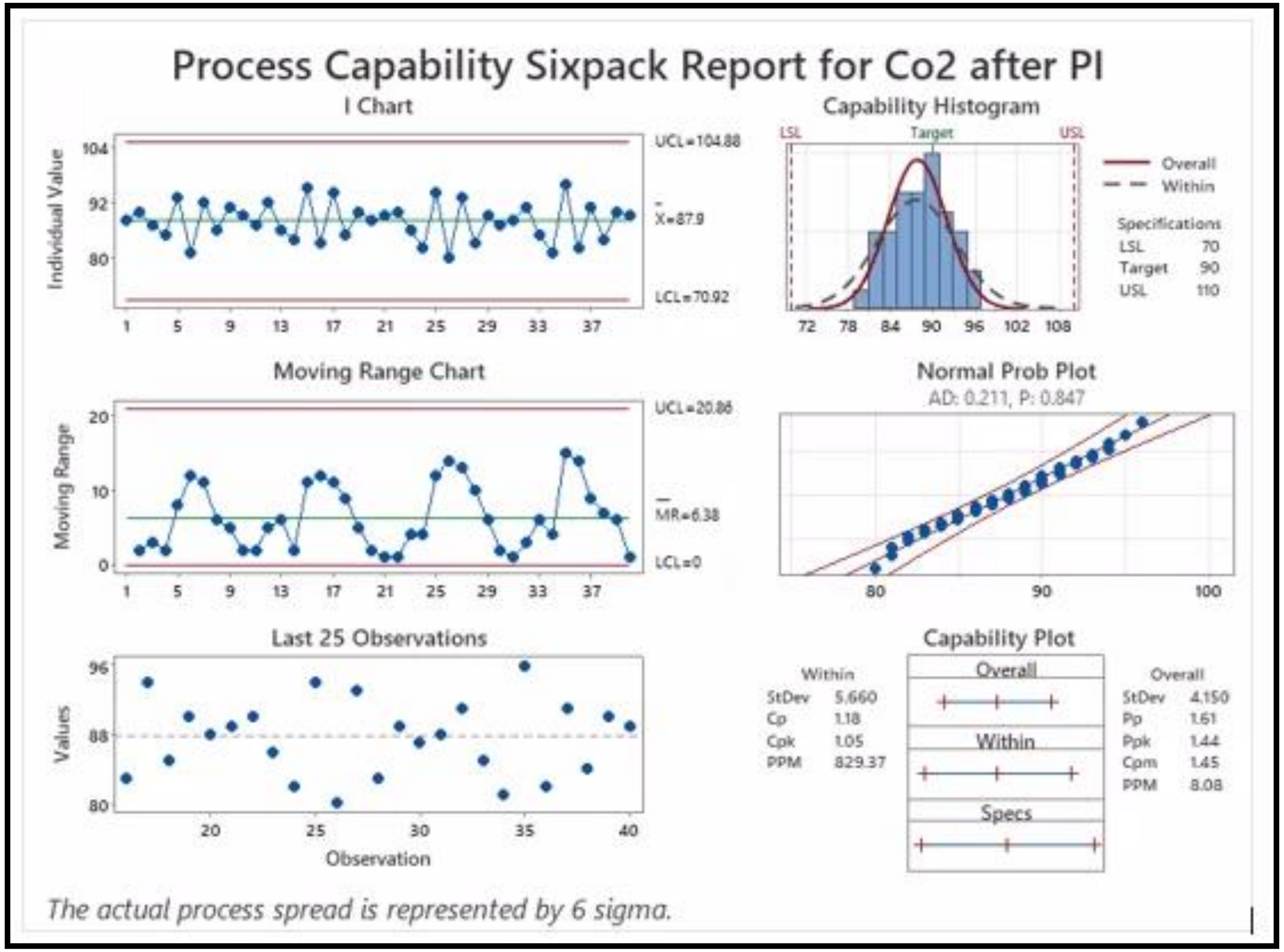
Implement a Smart Traffic Management System (STMS) which uses real-time data analytics to optimize traffic lights and reduce idling time.

Both Cp and Cpk values have improved. Cp has increased from 0.37 to 1.18, and Cpk has gone up from 0.18 to 1.05. This indicates the process spread is narrower relative to the specification limits and that the process mean is better centered between the LSL and USL. Now both indices are above 1, showing a capable process that can meet specifications more consistently.

The PPM > USL has dropped dramatically to 8.03, indicating that the number of units exceeding the USL has significantly decreased post-PI.

The implementation of a Smart Traffic Management System appears to have been effective in reducing CO2 emissions from vehicles, making the process much more capable than before

Six Pack Report



I Chart (Individual Value Plot):

The process is stable with most individual values falling within control limits, showing consistency over time with no signs of special cause variation.

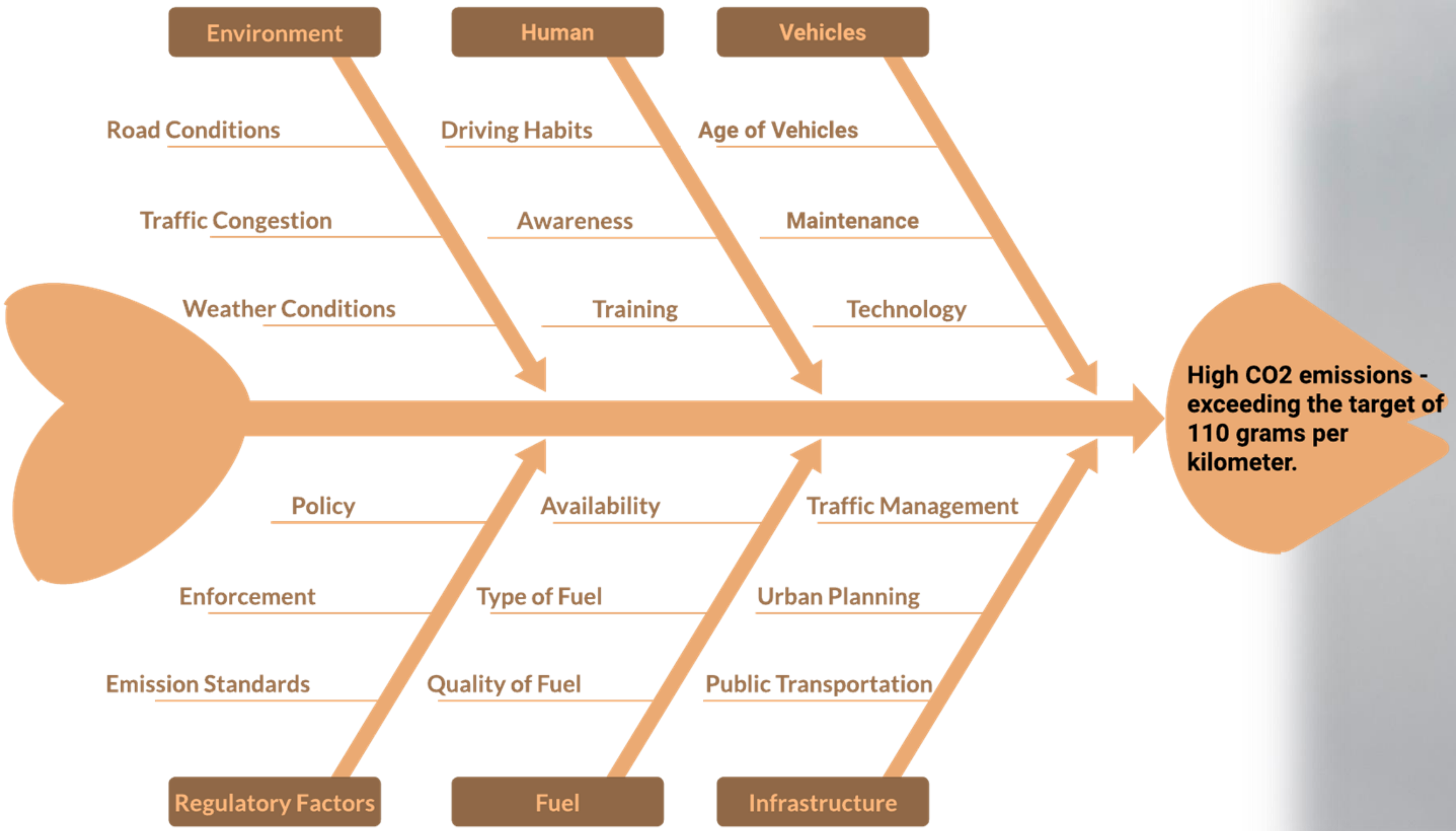
Normal Probability Plot:

The data points closely follow the straight line, suggesting that the emission data is normally distributed, a key assumption for many statistical analyses.

Capability Plot:

The Cp and Cpk values are both above 1, indicating a capable process, with Cp showing the process's ability to meet specifications and Cpk indicating that the process is centered between the limits. The process performance (Ppk) is also above 1, which further confirms the capability in the long run.

RCA : FISHBONE

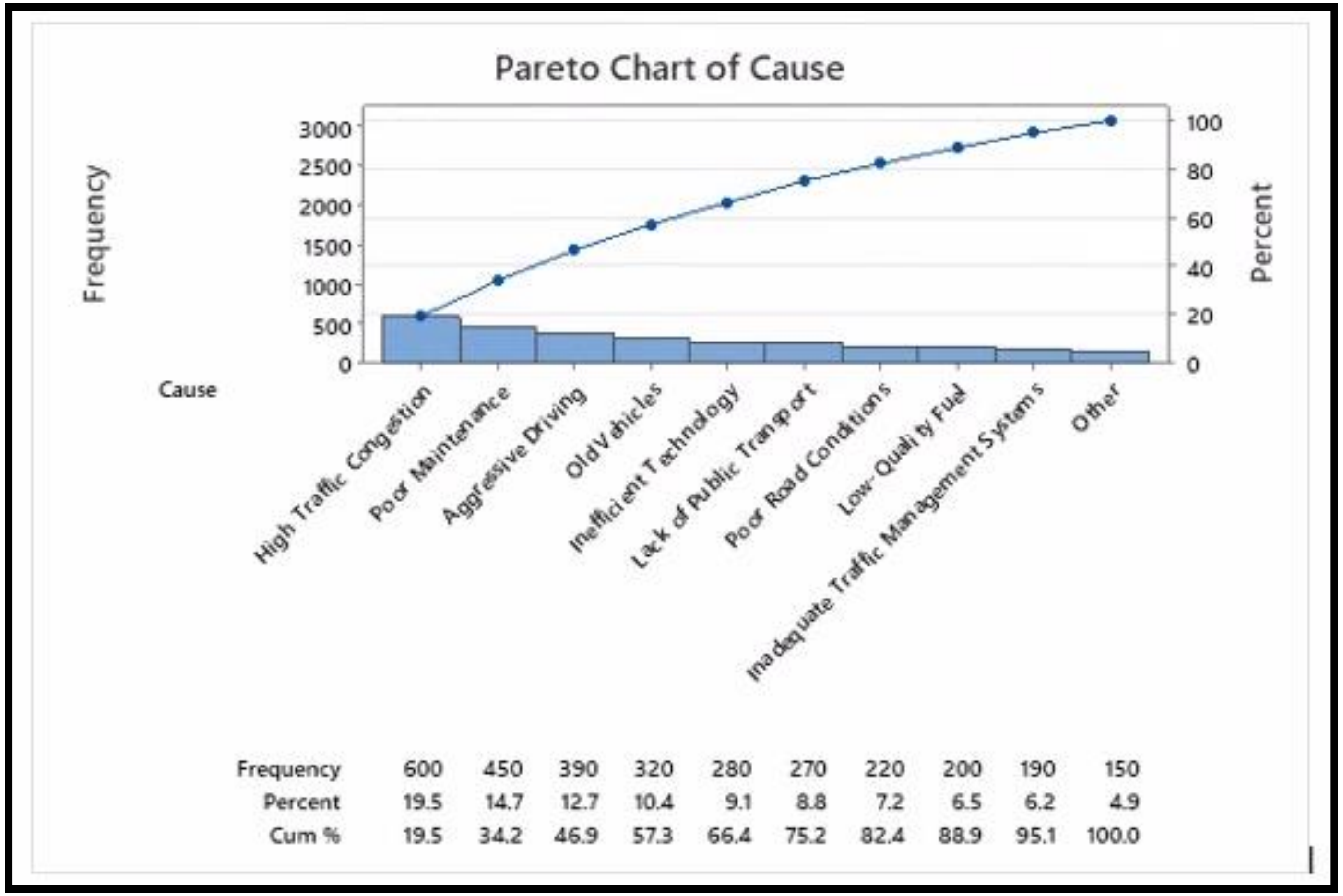


Pareto Chart

High Traffic Congestion is the leading cause of high vehicle emissions, accounting for approximately 19.5% of the total frequency. It’s a critical area to target for emission reduction strategies.

Poor Maintenance and Aggressive Driving are also substantial contributors, with about 14.7% and 12.7% of the frequency, respectively. These indicate behavioral and maintenance-related issues that could be addressed through public awareness campaigns and stricter vehicle maintenance regulations.

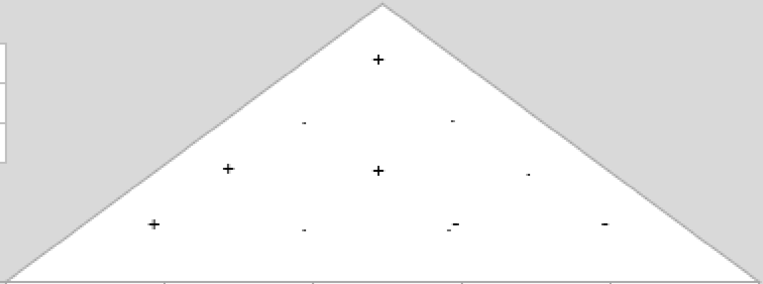
Old Vehicles and Inefficient Technology together make up around 22.1% of the total frequency, suggesting that there is significant potential for improvement by updating vehicle fleets and adopting newer, cleaner technologies.



The top three causes you could potentially mitigate about 46.9% of the problem.

Quality Function Deployment

Project title:	Climate Change Prevention/Mitigation
Project leader:	Shreyas Patil
Date:	4/10/2024



Correlation:

+	.	-
Positive	No correlation	Negative

Relationships:

9	3	1	
Strong	Moderate	Weak	None

Competitive evaluation (1: low, 5: high)

	1: low, 5: high Customer importance rating	Desired direction of improvement (↑,0,↓) Functional Requirements (How's) → Customer Requirements - (What's) ↓	smart traffic management systems	low-emission zones	electric vehicle charging stations	modernize public transit	emissions standards for vehicles	Weighted Score	Satisfaction rating	Competitor rating 1	Competitor rating 2	Competitor rating 3
1	5	Reduce overall CO2 emissions from vehicles.	9	9	3	3	9	165	4	3	2	2
2	5	Decrease average individual vehicle emissions.	3	9	1	1	9	115	3	4	1	4
3	4	Improve urban air quality indices	9	9	3	3	9	132	4	3	3	3
4	3	Increase adoption of renewable energy sources.	1	1	9	3	1	45	5	3	4	5
5	4	Enhance public transportation options and usage.	3	3	3	9	3	84	2	4	2	2
6								0				
7								0				
8								0				
9								0				
		Technical importance score	111	141	71	77	141	541				
		Importance %	21%	26%	13%	14%	26%	100%				
		Priorities rank	3	1	5	4	1					
		Current performance	3	3	2	4	4					
		Target	5	5	5	5	5					
		Benchmark	4	3	3	4	3					
		Difficulty	2	2	1	2	3	1: very easy, 5: very difficult				
		Cost and time	3	3	4	5	3	1: low, 5: high				
		Priority to improve	**5**	**4**	**4**	**3**	**4**					

Detailed Analysis of DOE on Climate Change Mitigation Factors

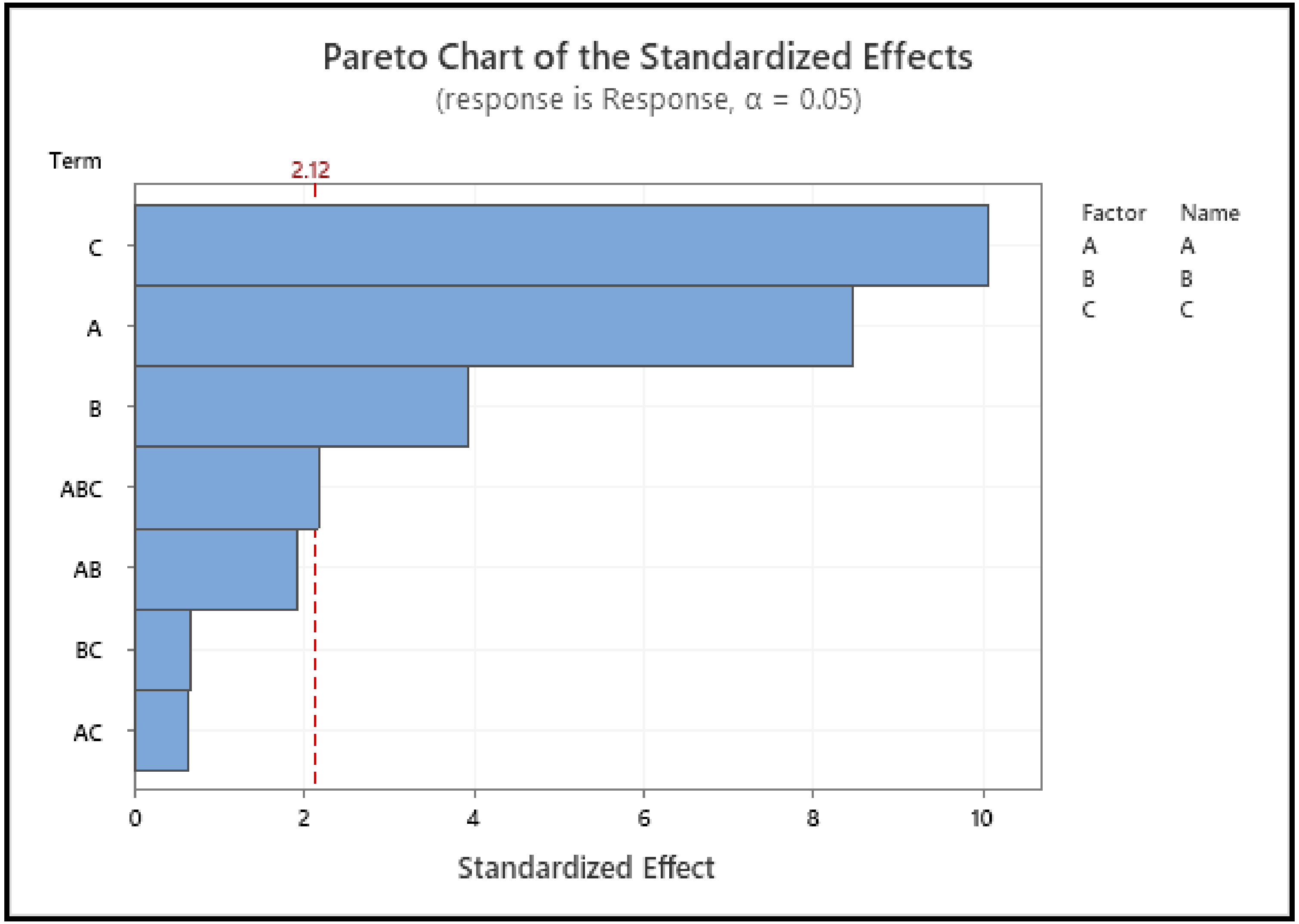
Climate change is a critical global issue influenced by various factors. In this study, a Design of Experiments (DOE) approach is utilized to systematically evaluate the impact of three significant factors on climate change mitigation: Carbon Dioxide Emission Levels (Factor A), Forest Cover (Factor B), and Renewable Energy Usage (Factor C). This analysis aims to understand the individual and combined effects of these factors on mitigating climate change

Methodology

A full factorial DOE was conducted, assessing the interactions and main effects of the three factors. Each factor was coded as follows for the analysis:

1. Factor A (**Carbon Dioxide Emission Levels**): Low (-1), High (+1)
2. Factor B (**Forest Cover**): Decreased (-1), Increased (+1)
3. Factor C (**Renewable Energy Usage**): Low (-1), High (+1)

The factorial design allowed for the examination of each factor's impact and the interaction effects between them.



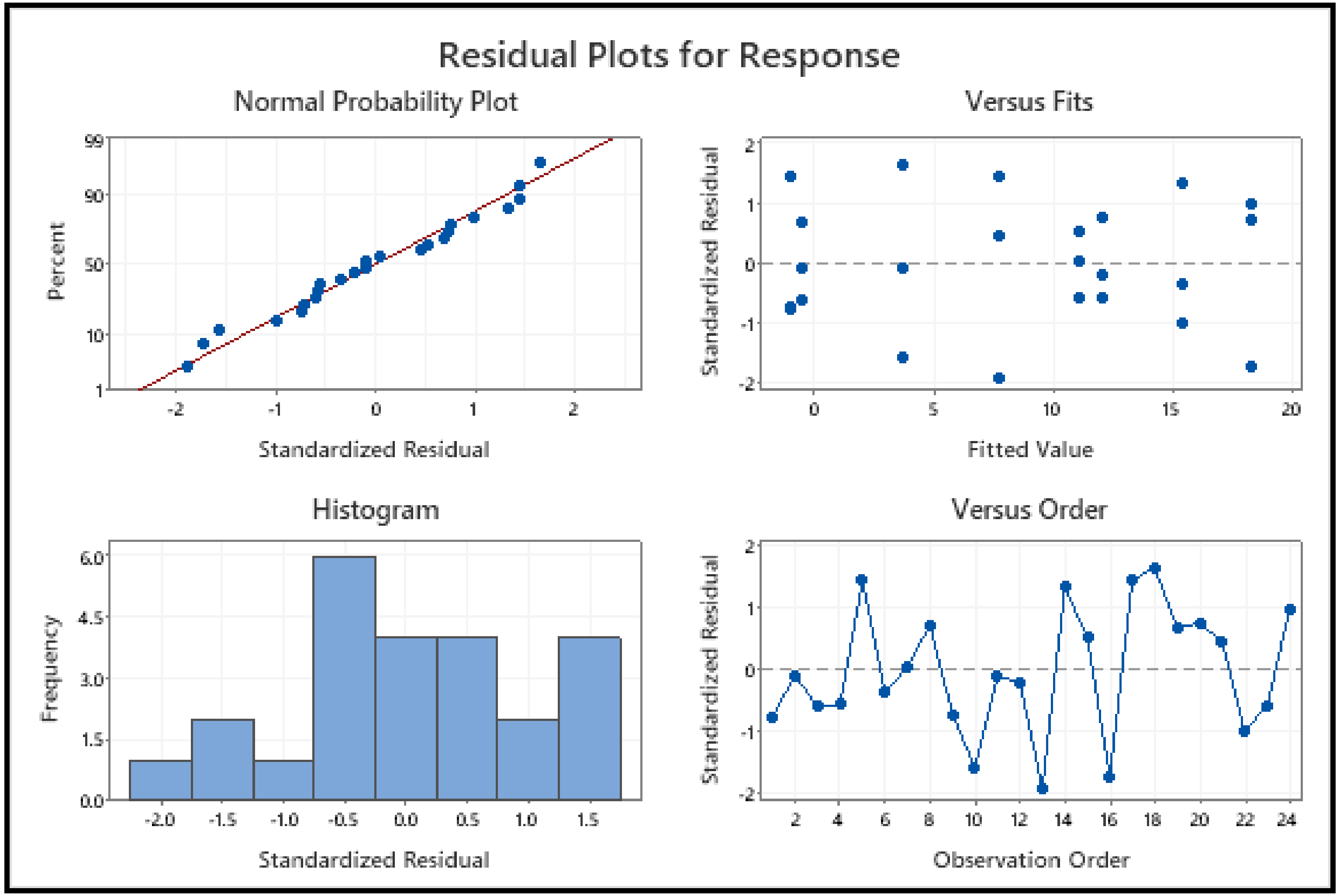
The Pareto chart of the standardized effects illustrates that in the context of climate change mitigation, Factor C (Renewable Energy Usage) stands out as the most influential, exceeding the significance threshold indicated by the vertical red dashed line. Factor A (Carbon Dioxide Emission Levels) also surpasses this threshold, showing a significant effect, while Factor B (Forest Cover), though impactful, is less significant compared to Factors A and C. Interaction effects, particularly the three-way interaction (ABC), and two-way interactions (AB, BC, AC) are below the significance threshold, suggesting they do not significantly influence the response variable at the 0.05 alpha level.

Normal Probability Plot (Top-Left): The residuals fall along the straight line quite well, which suggests that the residuals are normally distributed

Residuals Versus Fits Plot (Top-Right): There's no clear pattern or trend in the residuals as they're scattered randomly around the horizontal axis.

Histogram of Standardized Residuals (Bottom-Left): The histogram shows the distribution of the residuals. The shape is somewhat symmetric and bell-shaped

Residuals Versus Order Plot (Bottom-Right): This plot shows the residuals plotted against the time order of the observations. There doesn't appear to be any obvious pattern or cyclicality, suggesting that there is no autocorrelation in the residuals.



Factorial Regression: Response versus A, B, C

Coded Coefficients

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant		8.339	0.537	15.52	0.000	
A	8.079	4.039	0.537	7.52	0.000	1.00
B	3.753	1.876	0.537	3.49	0.002	1.00
C	9.622	4.811	0.537	8.95	0.000	1.00

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.63213	88.16%	86.38%	82.95%

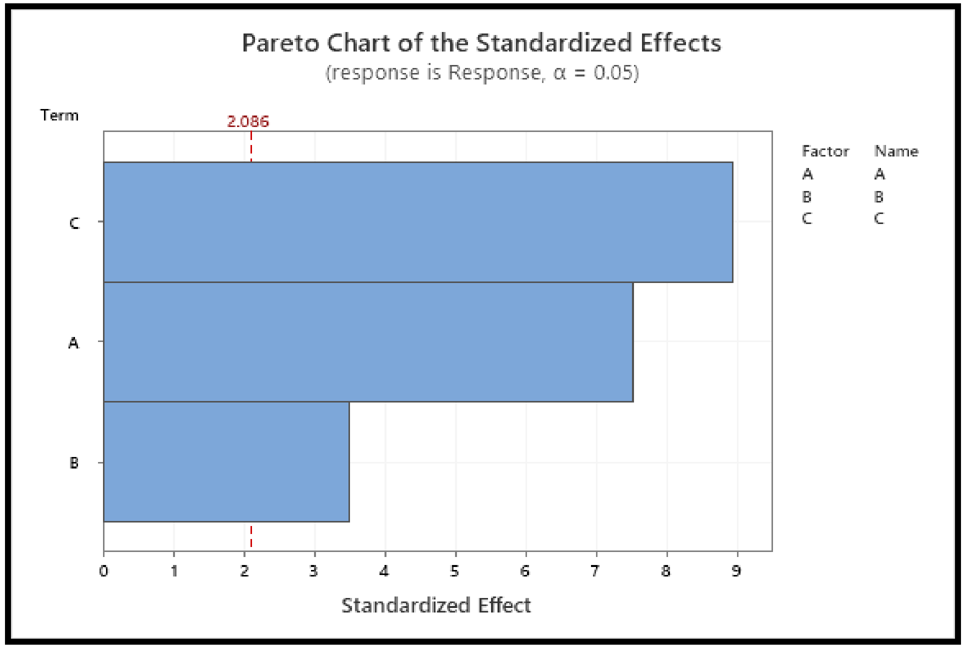
Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	3	1031.56	343.854	49.63	0.000
Linear	3	1031.56	343.854	49.63	0.000
A	1	391.58	391.578	56.52	0.000
B	1	84.49	84.491	12.20	0.002
C	1	555.49	555.494	80.18	0.000
Error	20	138.56	6.928		
Lack-of-Fit	4	51.04	12.760	2.33	0.100
Pure Error	16	87.52	5.470		
Total	23	1170.12			

In the factorial regression analysis, factors A (Carbon Dioxide Emission Levels), B (Forest Cover), and C (Renewable Energy Usage) significantly impact the response variable. Factor C has the most substantial effect, followed by A and then B.

Low p-values for all factors confirm their significant influence

The model's R-squared value of 88.16% indicates a strong explanatory power for the response variable



Renewable Energy Usage (C) is the most significant factor exceeding the reference line for a confidence level of 95%, indicating a strong impact on climate mitigation efforts

Overall Analysis

In the factorial regression focused on climate change mitigation, the effects of Carbon Dioxide Emission Levels (A) and Renewable Energy Usage (C) are statistically significant with effects of 8.079 and 9.622 respectively.

Interaction Effects:

The interaction between Factors A and B (A*B) showed a marginal significance ($p = 0.072$), suggesting that the combined impact of carbon dioxide emission levels and forest cover on climate change is notable but requires further investigation to fully understand its dynamics.

The three-way interaction (ABC) was significant ($p = 0.045$), pointing to a complex interrelationship between carbon dioxide emissions, forest cover, and renewable energy usage. This suggests that the most effective climate change mitigation strategy might require a holistic approach that considers all three factors simultaneously.

Coded Coefficients

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant		8.339	0.477	17.47	0.000	
A	8.079	4.039	0.477	8.46	0.000	1.00
B	3.753	1.876	0.477	3.93	0.001	1.00
C	9.622	4.811	0.477	10.08	0.000	1.00
A*B	1.838	0.919	0.477	1.93	0.072	1.00
A*C	-0.623	-0.311	0.477	-0.65	0.524	1.00
B*C	-0.649	-0.325	0.477	-0.68	0.506	1.00
A*B*C	-2.078	-1.039	0.477	-2.18	0.045	1.00

The Supply Chain Model (Lean)

The challenge lies in determining the optimal number of measurement stations required, along with the corresponding measurement device assemblies and support crews to operate these stations.

The weekly flow information

Item	Support Crews	Measurement Device Assembly	Measurement Stations
Production/Sale	9	10	8
Inventory Max	9	7	8
Cost of Inventory	1	3	5
Cost of Overflow	3	4	7
Cost of Shortage	5	6	8
Random/Selection	Judgement	Judgement	Distribution J

Week	Distribution J
1	5
2	3
3	6
4	8
5	8
6	6
7	5
8	7
9	6
10	9

Min no of Stations : 3
Max no of Stations : 10

Before :

Product	Level	Column1	1	2	3	4	5	6	7	8	9	10	Total
Measurement Stations	0	Demand (J1)	5	3	6	8	8	6	5	7	6	9	63
		Planned Receipt	8	8	7	6	4	5	7	6	5	5	61
		Total Units	16	16	15	14	10	7	8	9	7	6	108
		Inventory	8	8	8	6	2	1	3	2	1	-3	36
		Overflow	3	5	1	0	0	0	0	0	0	0	9
		Shortage	0	0	0	0	0	0	0	0	0	3	3
		Cost of Inventory	40	40	40	30	10	5	15	10	5	0	195
		Cost of Overflow	21	35	7	0	0	0	0	0	0	0	63
		Cost of Shortage	0	0	0	0	0	0	0	0	0	24	24
Measurement Device Assembly	1	Production	8	8	7	6	4	5	7	6	5	5	61
		Planned Receipt	8	8	7	6	4	5	7	6	5	5	61
		Total Units	15	15	14	13	11	12	14	13	12	12	131
		Inventory	7	7	7	7	7	7	7	7	7	7	70
		Overflow	0	0	0	0	0	0	0	0	0	0	0
		Shortage	0	0	0	0	0	0	0	0	0	0	0
		Cost of Inventory	21	21	21	21	21	21	21	21	21	21	210
		Cost of Overflow	0	0	0	0	0	0	0	0	0	0	0
		Cost of Shortage	0	0	0	0	0	0	0	0	0	0	0
Support Crews	2	Production	8	8	7	6	4	5	7	6	5	5	61
		Planned Receipt	8	8	7	6	5	5	4	6	5	5	59
		Total Units	17	17	16	15	14	14	13	15	14	14	149
		Inventory	9	9	9	9	9	9	9	9	9	9	90
		Overflow	0	0	0	0	0	0	0	0	0	0	0
		Shortage	0	0	0	0	0	0	0	0	0	0	0
		Cost of Inventory	9	9	9	9	9	9	9	9	9	9	90
		Cost of Overflow	0	0	0	0	0	0	0	0	0	0	0
		Cost of Shortage	0	0	0	0	0	0	0	0	0	0	0

Results-

COST	Level 0	Level 1	Level 2
Cost of Inventory	195	210	90
Cost of Overflow	63	0	0
Cost of Shortage	24	0	0
Cost/Level	282	210	90
Total Cost	582		

BEFORE

After :

Product	Level	Column1	1	2	3	4	5	6	7	8	9	10	Total
Measurement Stations	0	Demand (J1)	6	2	9	9	9	4	6	8	4	10	67
		Planned Receipt	2	0	3	9	4	4	7	7	4	10	50
		Total Units	10	4	5	9	4	4	7	8	4	10	65
		Inventory	4	2	-4	0	-5	0	1	0	0	0	-2
		Overflow	0	0	0	0	0	0	0	0	0	0	0
		Shortage	0	0	4	0	5	0	0	0	0	0	9
		Cost of Inventory	20	10	0	0	0	0	5	0	0	0	35
		Cost of Overflow	0	0	0	0	0	0	0	0	0	0	0
		Cost of Shortage	0	0	32	0	40	0	0	0	0	0	72
Measurement Device Assembly	1	Production	2	0	3	9	4	4	7	7	4	10	50
		Planned Receipt	2	0	3	9	4	4	7	7	4	10	50
		Total Units	12	10	13	19	14	14	17	17	14	20	150
		Inventory	10	10	10	10	10	10	10	10	10	10	100
		Overflow	0	0	0	0	0	0	0	0	0	0	0
		Shortage	0	0	0	0	0	0	0	0	0	0	0
		Cost of Inventory	30	30	30	30	30	30	30	30	30	30	300
		Cost of Overflow	0	0	0	0	0	0	0	0	0	0	0
		Cost of Shortage	0	0	0	0	0	0	0	0	0	0	0
Support Crews	2	Production	2	0	3	9	4	4	7	7	4	10	50
		Planned Receipt	2	0	3	9	5	4	4	7	4	10	48
		Total Units	11	0	3	9	5	4	4	7	4	10	57
		Inventory	9	0	0	0	0	0	0	0	0	0	9
		Overflow	0	0	0	0	0	0	0	0	0	0	0
		Shortage	0	0	0	0	0	0	0	0	0	0	0
		Cost of Inventory	9	0	0	0	0	0	0	0	0	0	9
		Cost of Overflow	0	0	0	0	0	0	0	0	0	0	0
		Cost of Shortage	0	0	0	0	0	0	0	0	0	0	0

Comparison-

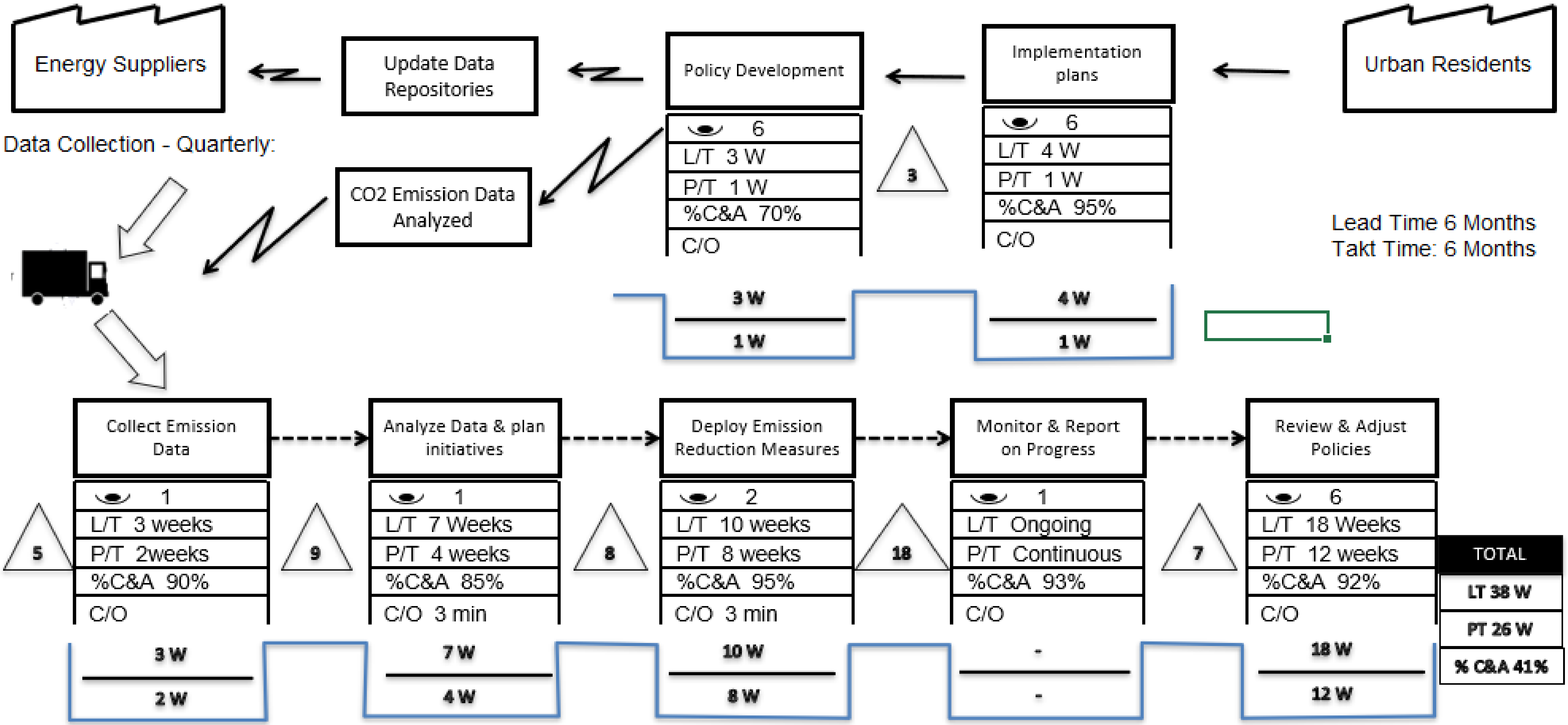
COST	Level 0	Level 1	Level 2
Cost of Inventory	195	210	90
Cost of Overflow	63	0	0
Cost of Shortage	24	0	0
Cost/Level	282	210	90
Total Cost	582		

BEFORE

Cost	Level 0	Level 1	Level 2
Cost of Inventory	35	300	9
Cost of Overflow	0	0	0
Cost of Shortage	72	0	0
Cost/Level	107	300	9
Total Cost	416		

AFTER

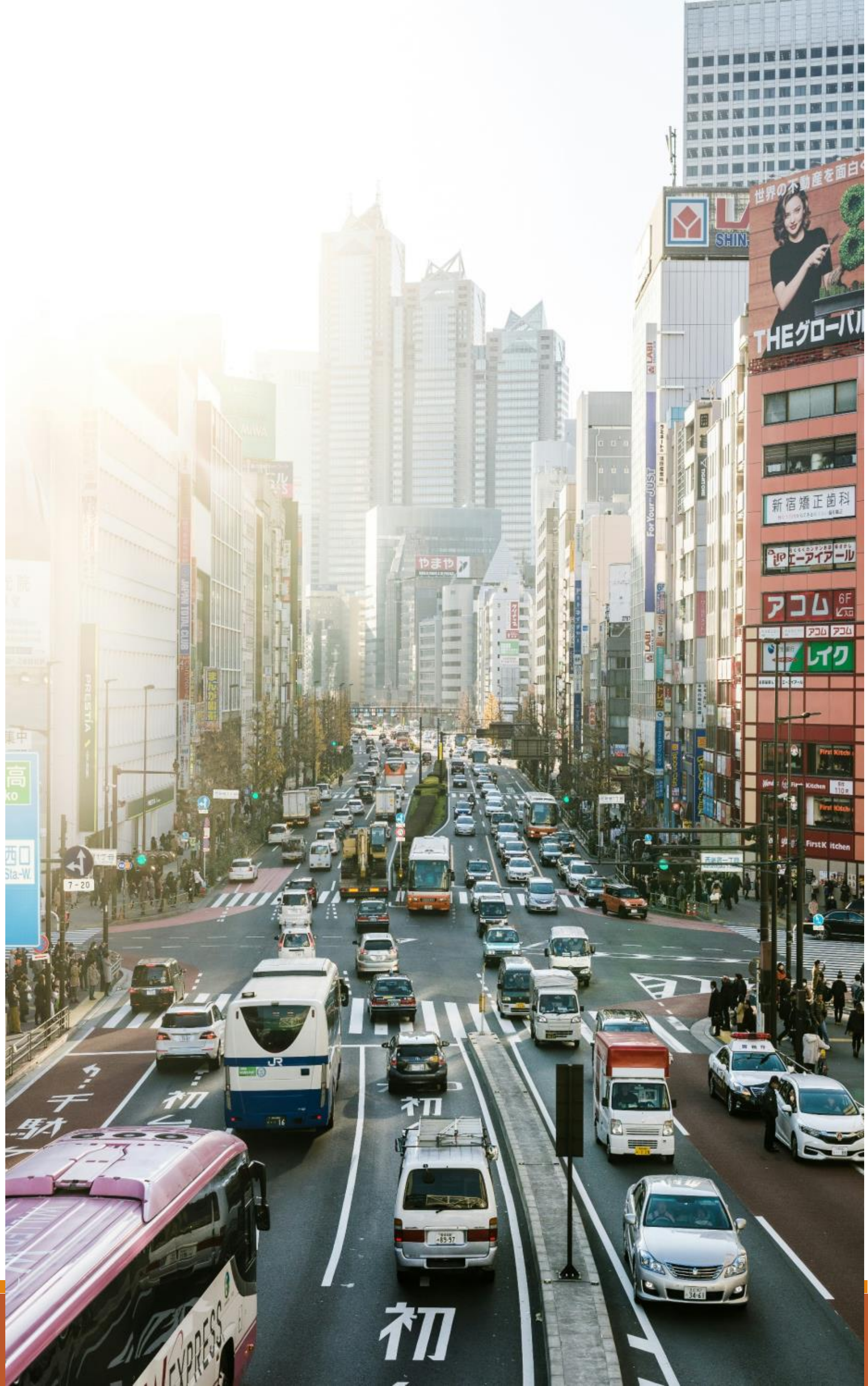
Value Stream Map

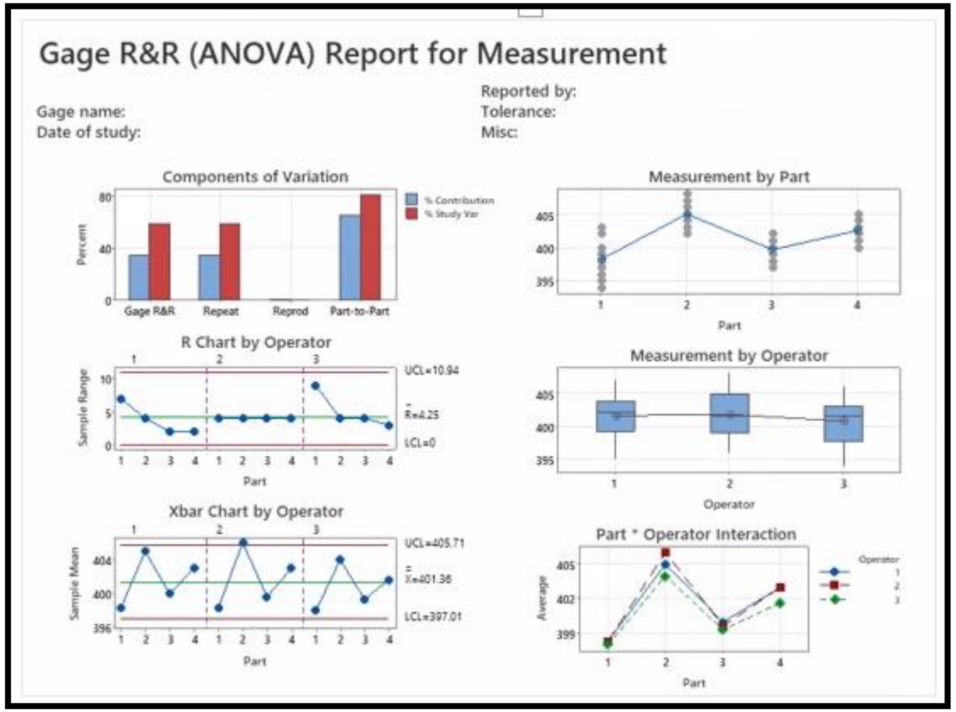


Gauge R&R Study

In our efforts to mitigate climate change, we have deployed CO_2 sensors across the urban area to monitor carbon emissions. There is a need to validate the measurement system's reliability to ensure the consistency and precision of these instruments. Therefore, a Gauge R&R study will be conducted.

For the Gauge R&R study, we will consider:
4 randomly selected CO_2 sensors (the 'parts' in the study).
3 operators who will each measure CO_2 levels with all sensors in identical conditions (the 'appraisers' in the study).
3 repeated measurements per sensor by each operator (the 'repeats' in the study).
The measurements will be taken in parts per million (ppm) of CO_2 in the air, which is the standard unit of measurement for this type of sensor.





Guage R&R

Two-Way ANOVA Table With Interaction

Source	DF	SS	MS	F	P
Part	3	246.528	82.1759	138.672	0.000
Operator	2	6.889	3.4444	5.813	0.039
Part * Operator	6	3.556	0.5926	0.107	0.995
Repeatability	24	133.333	5.5556		
Total	35	390.306			

α to remove interaction term = 0.05

Two-Way ANOVA Table Without Interaction

Source	DF	SS	MS	F	P
Part	3	246.528	82.1759	18.0093	0.000
Operator	2	6.889	3.4444	0.7549	0.479
Repeatability	30	136.889	4.5630		
Total	35	390.306			

Variance Components

Source	VarComp	%Contribution (of VarComp)
Total Gage R&R	4.5630	34.60
Repeatability	4.5630	34.60
Reproducibility	0.0000	0.00
Operator	0.0000	0.00
Part-To-Part	8.6237	65.40
Total Variation	13.1866	100.00

Gage Evaluation

Source	StdDev (SD)	Study Var (6 × SD)	%Study Var (%SV)
Total Gage R&R	2.13611	12.8167	58.82
Repeatability	2.13611	12.8167	58.82
Reproducibility	0.00000	0.0000	0.00
Operator	0.00000	0.0000	0.00
Part-To-Part	2.93661	17.6196	80.87
Total Variation	3.63134	21.7880	100.00

Part Variation:
There is significant variation between parts (sensors), with a P-value of 0.000 in both ANOVA tables

Operator Variation:
There is a statistically significant difference between operators (P = 0.039). However, when the interaction is removed, this significance disappears (P = 0.479), suggesting that the initial operator effect might be due to interactions with the parts.

Repeatability:
The repeatability, contributes 34.60% to the total variance. This is quite high and indicates that a single operator taking measurements multiple times may obtain significantly different readings.

Reproducibility:
Reproducibility, is not contributing to measurement system variation, which is a good indication of consistency among operators.

Gauge R&R Study - Analysis

<u>Part Variation:</u>

Cause: High variability between or issues with sensor storage or handling.

Remedy: Standardize sensor specifications and tighten quality control during manufacturing. Implement strict handling and storage protocols.

<u>Operator Variation:</u>

Cause: Differences might be influenced by how operators interact with the sensors.

Remedy: Standardize training for all operators to ensure consistency

<u>Repeatability:</u>

Cause: The measurements taken by a single operator are inconsistent.

Remedy: Check and calibrate measurement instruments regularly to ensure accuracy and reliability.

<u>Reproducibility:</u>

Cause: Good reproducibility indicates that variability among different operators is low, which is positive but may mask issues observable only at individual levels due to the repeatability problem.

Acceptance Sampling

The project involves receiving batches of air quality sensors that will be deployed across an urban area to measure pollutants as part of a climate monitoring initiative.

- Lot Size (N): Total number of sensors in each delivery, say 1,000 sensors.
- Producer's Risk (α): The risk you (as the buyer) are willing to take - 0.05.
- Consumer's Risk (β): 0.10.
- Acceptable Quality Level (AQL): - around 0.01 or 1% defective.
- Lot Tolerance Percent Defective (LTPD): - 0.05 or 5%
- Sample Size (n): 80 sensors. (from Nomograph)
- Acceptance Number (c): 2. (from Nomograph)

Operating Characteristic (OC) Curve

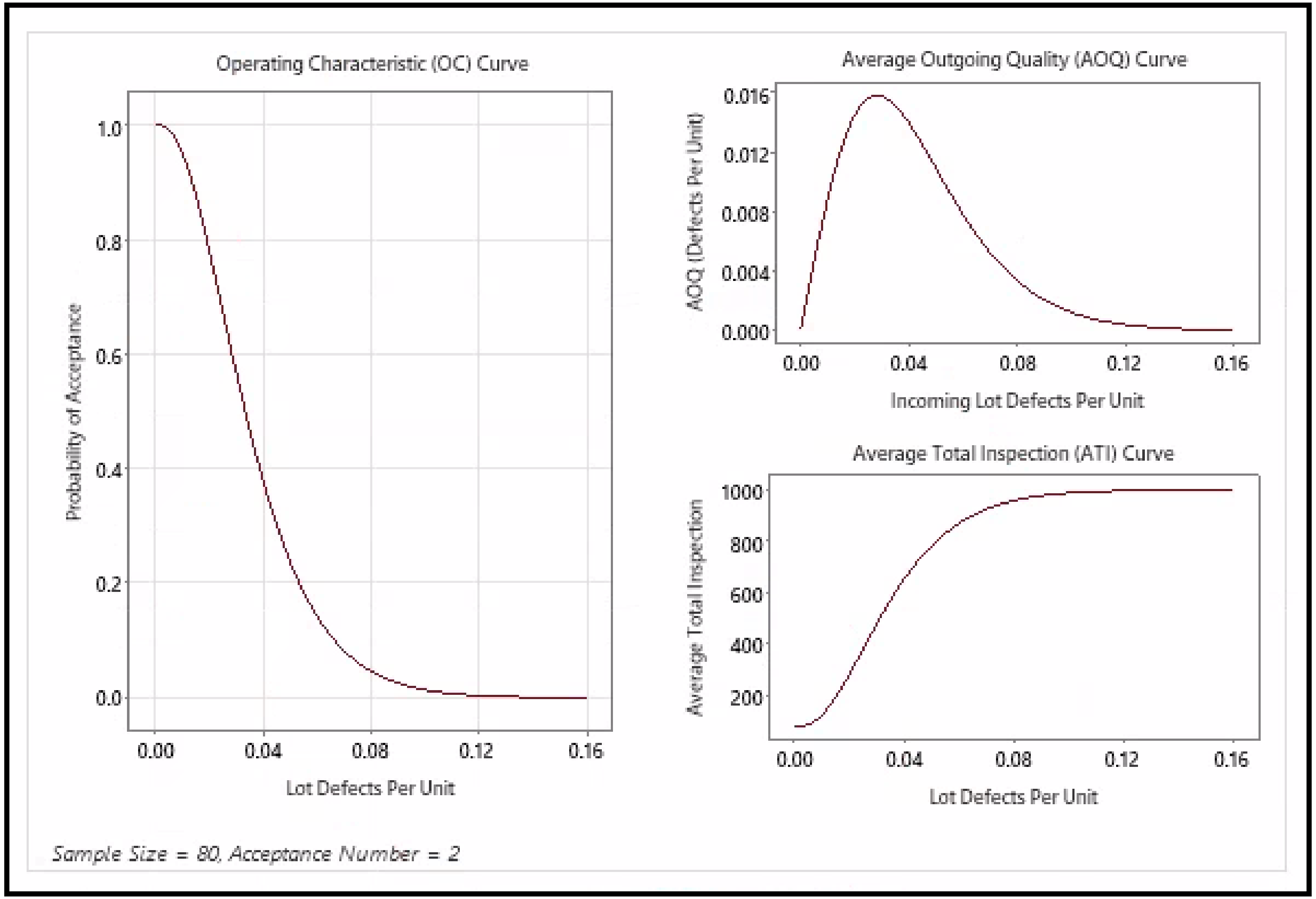
It shows that as the lot defect percentage increases, the probability of accepting the lot decreases. For a lot with a 1% defect rate, the curve suggests a very high likelihood of acceptance (close to 1), which drops as the defect rate increases

Average Outgoing Quality Curve

The peak of the AOQ curve represents the highest potential average quality that the inspected lots could have after rejecting and potentially replacing defectives based on the acceptance sampling plan.

Average Total Inspection Curve

It suggests that as the incoming lot quality worsens (defect rates increase), more items are inspected on average, likely due to an increase in lot rejections and the need for more inspections or re-inspections



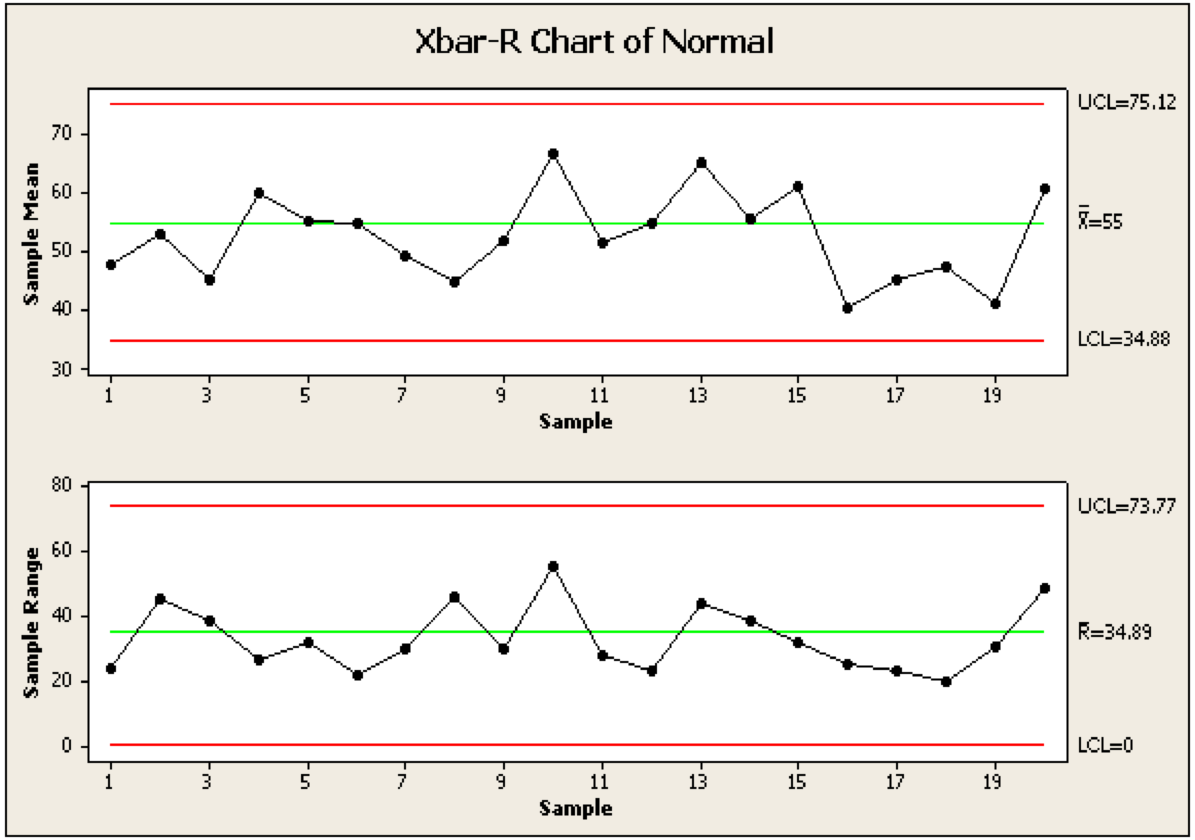
Statistical Process Control – X Bar-R

The Xbar chart displays the average CO_2 emission levels of subgroups collected over 19 time periods, which could represent weekly averages from various locations within the urban area.

The central line ($\bar{X}$) indicates the overall process mean for CO_2 emissions, which serves as a benchmark for comparing individual subgroup averages. None of the individual points fall outside the control limits, which suggests that individual CO_2 measurements are within the expected range of variability and the process is in control. However, there's noticeable fluctuation which might warrant further investigation.

The R chart reflects the range of CO_2 emissions within each subgroup, highlighting the spread of the data and indicating the consistency of the emission levels.

A consistent R chart, where all points fall within the control limits (UCL and LCL for the range), suggests that the variability in CO_2 emissions is stable and predictable across the subgroups.



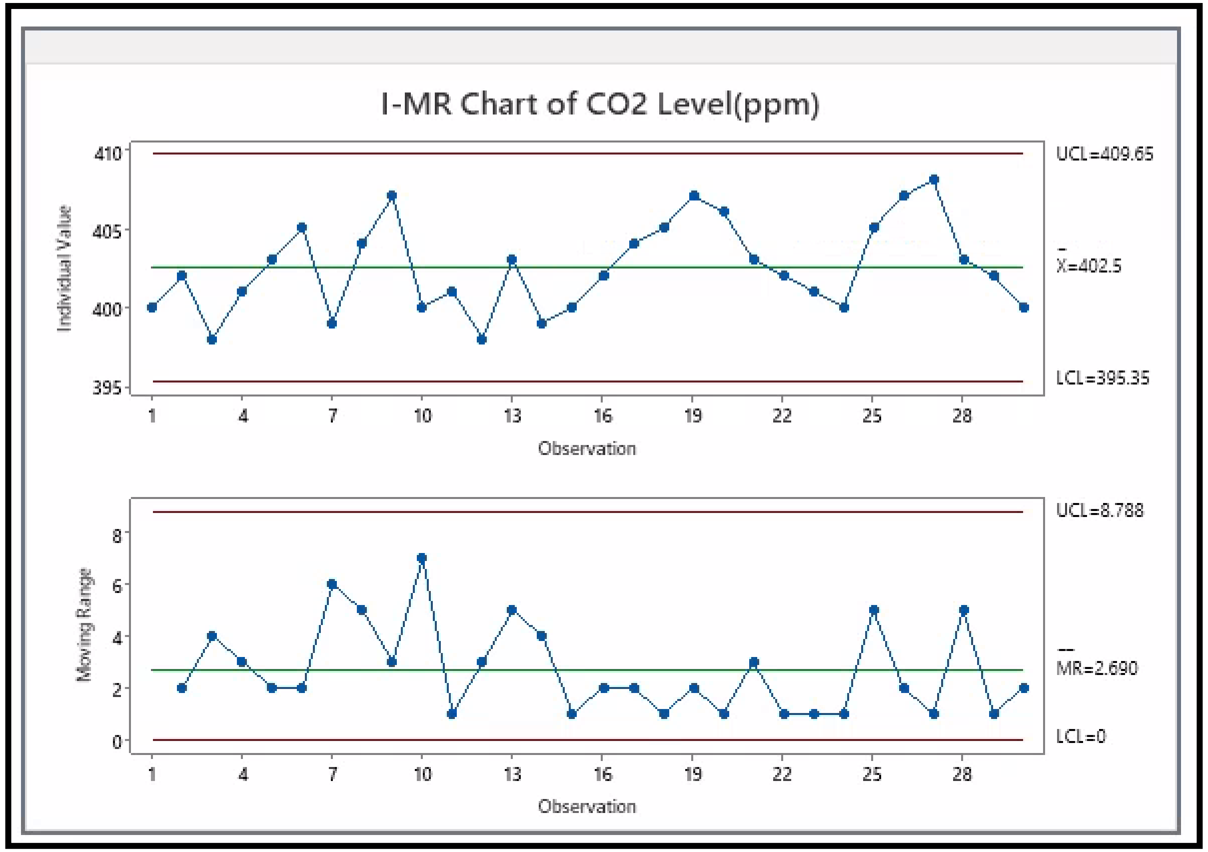
Statistical Process Control – I-MR Chart

This chart plots the individual observations of CO2 levels over time.

The central line (X-bar) represents the average CO2 level across all observations, which is approximately 402.5 ppm. The Upper Control Limit (UCL) and Lower Control Limit (LCL) are set at approximately 409.65 ppm and 395.35 ppm, respectively.

None of the individual points fall outside the control limits, which suggests that individual CO2 measurements are within the expected range of variability and the process is in control. However, there's noticeable fluctuation which might warrant further investigation.

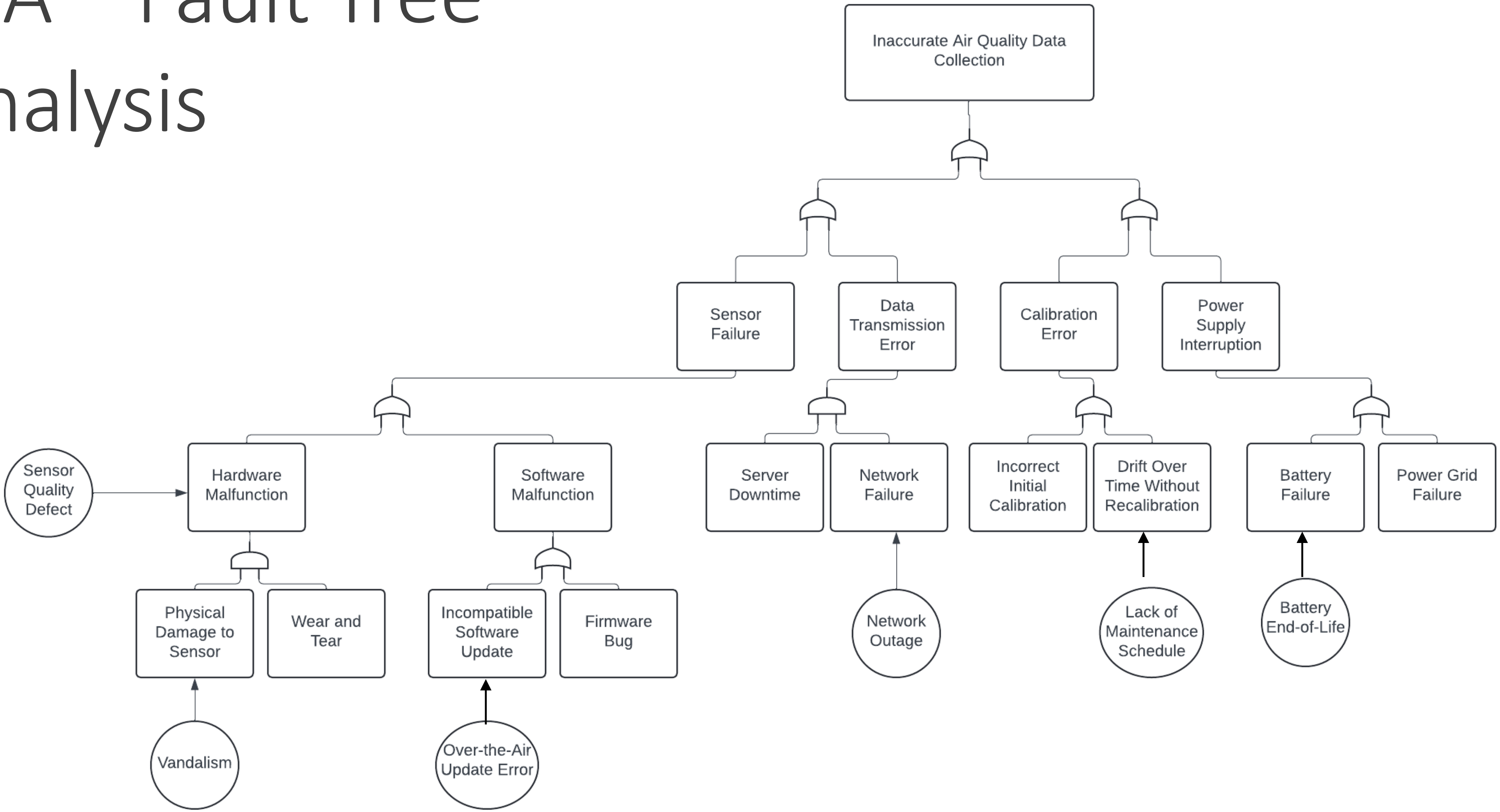
The I-MR (Individuals-Moving Range) chart is used here instead of an Xbar or P chart because the data represents individual measurements rather than subgroups



FMEA

Item	Potential Failure Mode	Potential Effect(s) of Failure	Severity (S)	Potential Cause(s) of Failure	Occurrence (O)	Current Control(s)	Detection (D)	RPN
Air Quality Sensor	Sensor reading inaccuracy	Incorrect data leads to poor policy decisions	9	Calibration drift, sensor degradation	4	Regular calibration checks, quality control at manufacturing	6	216
Air Quality Sensor	Power failure	Data gaps leading to incomplete data sets	7	Battery failure, power supply disruption	3	Battery life monitoring, backup power supply	5	105
Air Quality Sensor	Data transmission failure	Loss of real-time data, delays in data analysis	8	Network outage, hardware failure	3	Network redundancy, routine hardware checks	4	96
Air Quality Sensor	Physical damage	Sensor goes offline, missing measurements	6	Vandalism, weather damage	2	Protective casing, secure installation	5	60
Data Analysis Software	Incorrect data processing	Misleading information presented to policymakers	10	Software bug, user input error	2	Code review, user training	3	60
Installation Process	Improper installation	Sensor malfunctions or incorrect data	8	Improper handling, incorrect setup	3	Installation guidelines, installer training	7	168
Maintenance Procedure	Inadequate maintenance	Reduced sensor lifespan, inaccurate readings	7	Infrequent maintenance, untrained staff	3	Maintenance schedule, staff certification	5	105

FTA – Fault Tree Analysis



Improvements & Conclusion

Improvements

Continuous improvement is integral to the success of our urban greening initiative. The data-driven approach we've taken, particularly with the application of Statistical Process Control (SPC) techniques, highlights the need for iterative recalibration of our air quality sensors to ensure accurate readings. Enhancing network redundancy and investing in robust weatherproofing measures for our sensors will also mitigate the risks of data transmission failures and physical damage. Proactive maintenance schedules and staff training are recommended to address potential drifts in sensor calibration and to preserve the integrity of our data collection process over time.

Conclusion

In conclusion, the systematic examination of our climate project's processes through various statistical and analytical methods has provided a comprehensive understanding of our current capabilities and areas for improvement. The FMEA highlighted critical points of potential failure, enabling us to put preemptive measures in place to ensure the reliability of our air quality sensors. Moreover, the Fault Tree Analysis allowed us to delve deeper into the root causes of potential inaccuracies in data collection, leading to a strategic framework for mitigating these risks.

The SPC analysis, particularly the I-MR chart, has reinforced the stability and control we maintain over the process, with all individual measurements falling within expected control limits. This confirms the effectiveness of our current operational procedures and sets a benchmark for ongoing quality control

Thank you!

SYRACUSE UNIVERSITY