



CAPSTONE PROJECT

Forecasting Optic Fiber Deployment for enhanced Revenue Planning

Archit Handa (22f2000744)

Business Overview

(STU)

Sterlite Technologies Limited (STL) is a global optical and digital solutions company, which aims to deliver end-to-end data network solutions to its clients. STL currently operates in the B2B segment.

Project Focus:

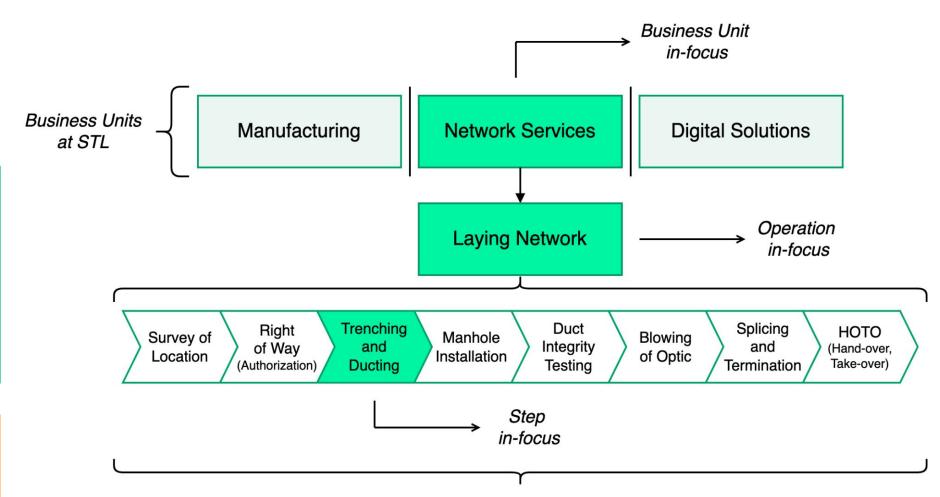
Trenching and Ducting (T&D), a crucial step in laying out optic fiber, thus in Capacity and overall Revenue Planning for the Organisation

Business Problem:

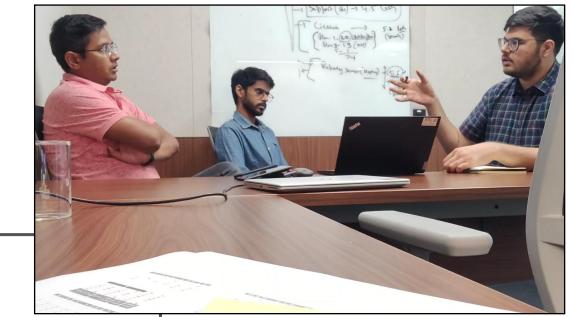
Inability to estimate optic fiber layout output for a month leading to deviations from Revenue Projections which causes delays in Turn Around Time (TAT) and Resource Wastage.

Solution:

Machine Learning Model that integrates concepts of Linear Regression and Time Series Analysis.



Entire Process of Laying out an Optic Fibre Network

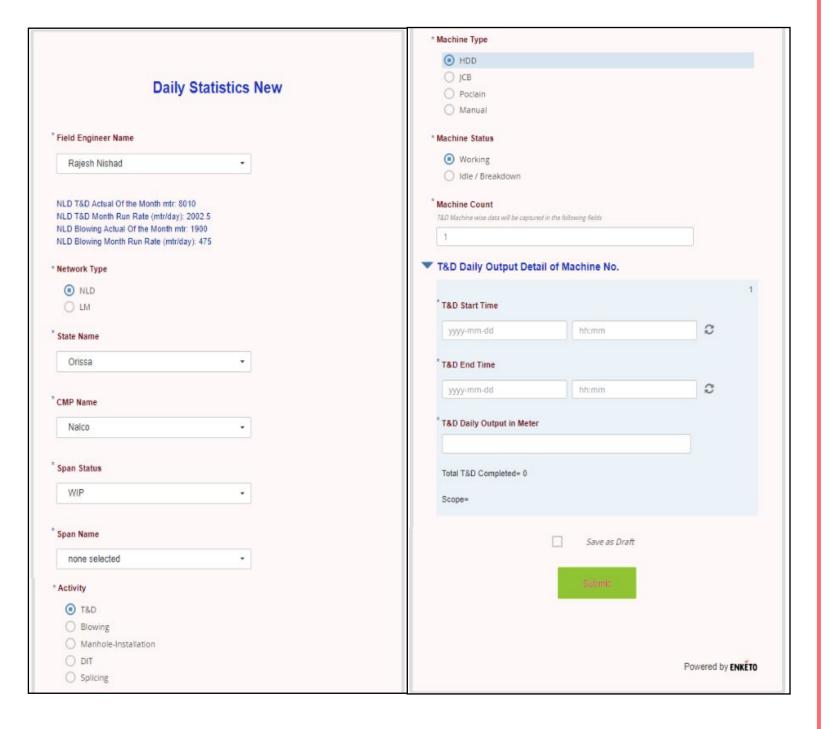


People of Contact: –

- Mr. Pankaj Singh
 PMO Lead at STL
- Mr. Shailendra Kumar
 PMO Analytics Engineer at STL

Data Collection

- Data collected using STL's in-house tool:
 FieldForce
- Daily details input by Field Engineer
- Data collected from October 2021 till date



Data Preprocessing

Step 1: Imputation

- Unusable fields were dropped such as Field Engineer Details
- Missing values were filled according to patterns exhibited
- First 3-month data was extremely noisy due to field engineers' unawareness regarding the tool → Dropped for further analysis

Step 2: Aggregation

- Current state captures **span-wise data**; however, **planning** is to be performed for **all spans in the country as a whole**
- Daily Statistics allow granularity; however, from modeling perspective, can cause the estimator to overfit

Step 3: Feature Engineering

- Work Duration = Machine End Time Machine Start Time
- Daily Productivity = Daily Output (in meter) / Machine Count

							9	Trenching_ And_Ducti	Trenching_ And_Ductin	Trenching_An d_Ducting_Dai	
	State_Nam				Machine_Ty	Machine_Stat	Machine	ng_Start_T	g_End_Tim	ly_Output_in_	Scope_k
_device = FE_Name	= e =	CMP_Name =	Span_Name =	Activity	pe =	us =	_Count	ime	e -	Meter =	ms =
FieldForce:	Meghalaya	Shillong	AS-NE Border-1 to NE-AS Bo	Trenching-and-Ducting	HDD	Working		2 2023-09-08	3: 2023-09-08 1	2 610	23.0
FieldForce:	Meghalaya	Shillong	AS-NE Border-1 to NE-AS Bo	Trenching-and-Ducting	HDD	Working	1	2 2023-09-08	3: 2023-09-08 1:	2 610	23.0
FieldForce:r	MP	Ujjain	Moman Badodiya-Bhaisoda	Trenching-and-Ducting	JCB	Idle-Breakdown	0	1		3	
fieldForce:r	MP	Ujjain	Nalkheda (NP)-Kayra	Trenching-and-Ducting	JCB	Idle-Breakdown		1		9	
ieldForce:	MP	Khargone	Mohana-Bagarda	Trenching-and-Ducting	JCB	Working	(i	1 2023-09-06	5: 2023-09-06 1:	2 300	18.5
ieldForce:	MP	Khargone	Mohana-Bagarda	Trenching-and-Ducting	JCB	Working	4	1 2023-09-07	1: 2023-09-07 1:	2 200	18.5
ieldForce:	Orissa	Bhawanipatna	Titlagarh-Sirol	Trenching-and-Ducting	HDD	Working	·	1 2023-09-08	3: 2023-09-08 1°	1 310	21.01
eldForce:9	MP	Chhindwara	Dongariya-Garra (CT)	Trenching-and-Ducting	HDD	Working		1 2023-09-08	5: 2023-09-08 1:	2 70	11.36
ieldForce:	MP	Chhindwara	Patan-Lakhnadon	Trenching-and-Ducting	Poclain	Idle-Breakdown	7	1		0.	
ieldForce:4	Orissa	Rayagada	Sorispadar-Parajasuku	Trenching-and-Ducting	HDD	Working		1 2023-09-08	5: 2023-09-08 1:	2 160	
TL:bgVlvM	Orissa	Rayagada	Balimela-Balimela	Trenching-and-Ducting	Manual	Working	(X	2023-09-08	2: 2023-09-08 0	180	0.0
ieldForce:f	MP	Ratlam	Rawti-Ratlam	Trenching-and-Ducting	JCB	Working		1 2023-09-08	3: 2023-09-08 1°	1 100	27.0
ieldForce:\	MP	Shahdol	Sheori Chandas-Purga	Trenching-and-Ducting	HDD	Working	0	1 2023-09-08	1: 2023-09-08 1:	3 300	49.74
ieldForce:k	Orissa	Bhawanipatna	Telenpali-Badbanjipali	Trenching-and-Ducting	HDD	Working	G.	1 2023-09-07	3: 2023-09-07 1:	3 310	22.12
ieldForce:k	Orissa	Bhawanipatna	Telenpali-Badbanjipali	Trenching-and-Ducting	HDD	Working		1 2023-09-08	2: 2023-09-08 1	3 240	22.12
FieldForce:	Orissa	Keonjhar	Jalahari-Jaroli	Trenching-and-Ducting	JCB	Idle-Breakdown		1	i a stat	6	

Raw Data before Processing

Data Tools

MS Excel, Pandas, Numpy, Scikit-Learn

JCB_ JCB_ JCB_ JCB_



Poclain_ Poclain_ Poclain_

Date	Scope	Count	Hours	Output	Productivity	Count	Hours	Output	Productivity	Count	Hours	Output	Productivity	Output	Hours	Count	Productivity
2022-01-01	410070.33	5	36.38	1980	396.00	5	22.52	650	130.00	2	2.02	0	0.00	2630	60.92	12	219.1
2022-01-02	406919.00	5	37.20	1700	340.00	7	48.43	1500	214.29	3	20.25	110	36.67	3310	105.88	15	220.6
2022-01-03	400914.00	8	57.80	3050	381.25	7	35.28	975	139.29	2	15.03	60	30.00	4085	108.12	17	240.29
2022-01-04	394909.00	6	35.27	1000	166.67	9	58.72	1812	201.33	3	8.77	100	33.33	2912	102.75	18	161.78
2022-01-05	388904.00	8	49.90	1540	192.50	8	49.07	1595	199.38	3	3 24.92	450	150.00	3585	123.88	19	188.68
2022-01-06	382899.00	6	45.73	1290	215.00	10	59.65	1712	171.20	3	16.85	0	0.00	3002	122.23	19	158.00
2022-01-07	376894.00	6	44.62	1420	236.67	8	54.00	1625	203.13	2	2.80	0	0.00	3045	101.42	16	190.3
2022-01-08	370889.00	5	37.63	2300	460.00	9	53.25	1694	188.22	2	7.95	150	75.00	4144	98.83	16	259.00
2022-01-09	364884.00	5	37.53	1750	350.00	11	68.88	2400	218.18	1	10.00	0	0.00	4150	116.42	17	244.12
2022-01-10	358879.00	8	64.77	2225	278.13	8	51.83	2205	275.63	2	15.13	200	100.00	4630	131.73	18	257.22
2022-01-11	353752.33	7	58.97	2490	355.71	8	49.25	2245	280.63	2	23.02	100	50.00	4835	131.23	17	284.4
2022-01-12	348625.67	6	40.78	1640	273.33	10	60.63	3176	317.60	2	20.78	200	100.00	5016	122.20	18	278.6
2022-01-13	343499.00	5	46.92	1530	306.00	7	35.98	2111	301.57	3	3 27.27	300	100.00	3941	110.17	15	262.73
2022-01-14	338372.33	6	49.32	1640	273.33	6	32.32	2107	351.17	2	12.00	0	0.00	3747	93.63	14	267.6
2022-01-15	333245.67	6	50.23	1330	221.67	6	34.02	2019	336.50	3	25.33	470	156.67	3819	109.58	15	254.60
2022-01-16	328119.00	5	47.65	1660	332.00	6	34.07	1980	330.00	2	19.05	0	0.00	3640	100.77	13	280.00
2022-01-17	322882.00	4	36.53	1400	350.00	8	39.82	2750	343.75	3	22.08	200	66.67	4350	98.43	15	290.00
2022-01-18	316694.33	5	44.45	850	170.00	10	64.93	3749	374.90	3	30.83	100	33.33	4699	140.22	18	261.0
2022-01-19	310506.67	4	35.58	1300	325.00	7	59.67	2364	337.71	2	8.73	150	75.00	3814	103.98	13	293.38
2022-01-20	306896.67	7	61.18	2071	295.86	7	39.08	2252	321.71	2	17.25	0	0.00	4323	117.52	16	270.19
2022-01-21	303286.67	5	46.73	1593	318.60	5	43.00	2640	528.00	2	18.50	0	0.00	4233	108.23	12	352.7
2022-01-22	300938.33	7	62.23	1545	220.71	7	44.45	2485	355.00	2	17.50	0	0.00	4030	124.18	16	251.8

HDD_ HDD_ HDD_

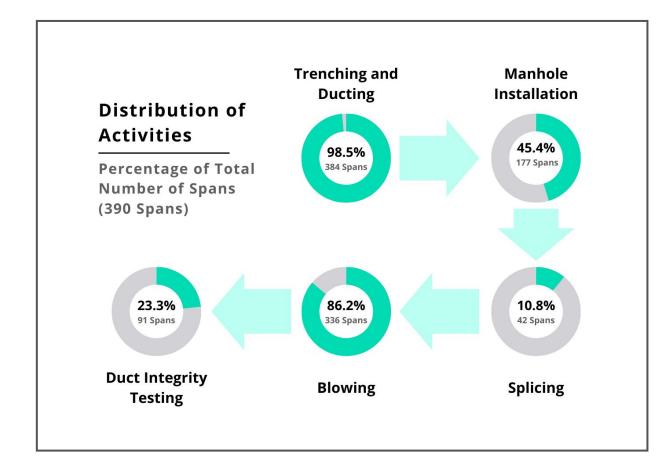






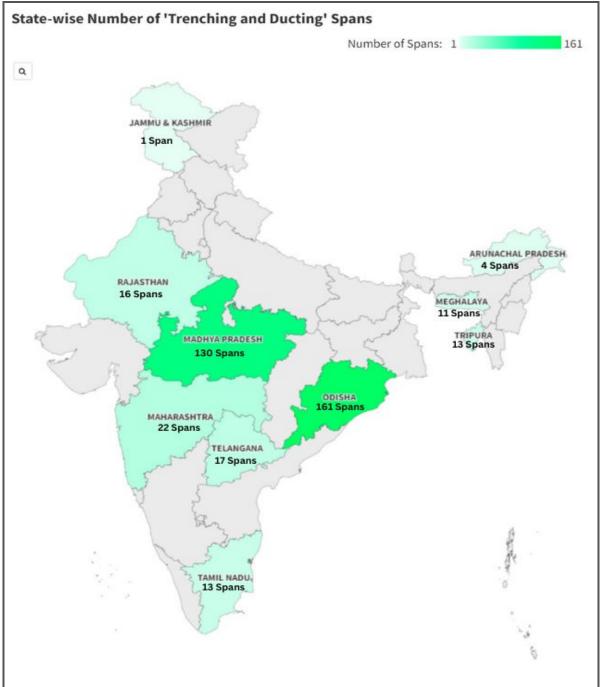
Total_ Total_ Total_

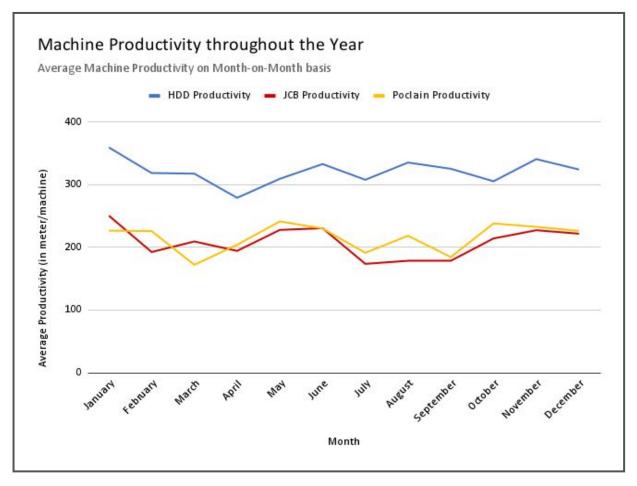
Descriptive Statistics



- Manhole Installation, Splicing, and DIT are quick to execute
- T&D and Blowing go hand-in-hand with a 10-day lag
- Significant Weight of T&D in Overall Capacity Planning

- Data available from various soil and weather landscapes
- Positive from a modeling viewpoint

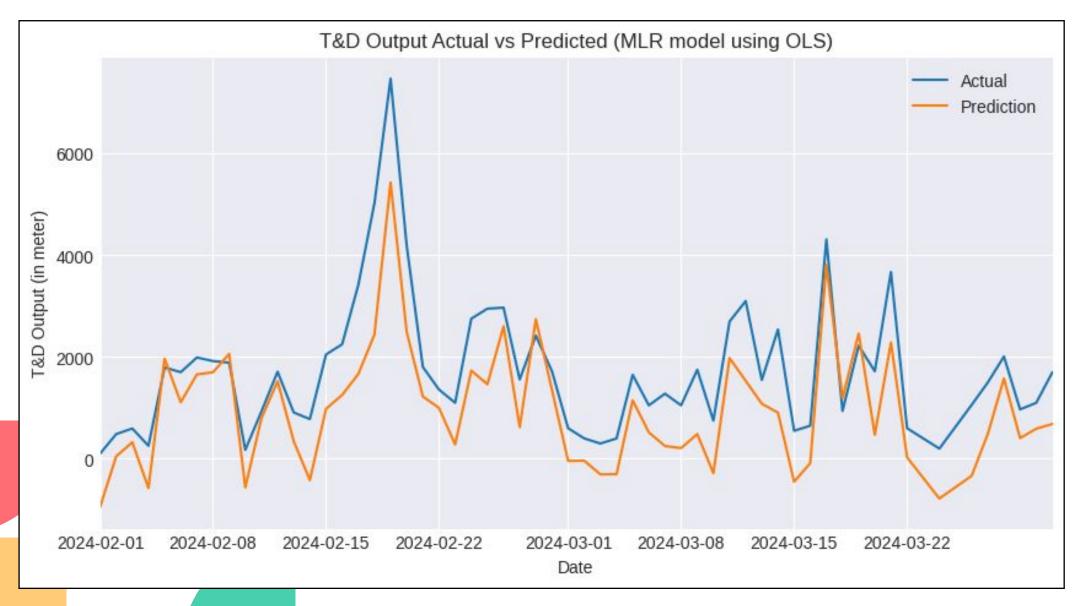




- HDD has highest productivity
- Fluctuations hint at certain cyclical patterns that should be decoded



Linear Regression: MLR OLS



Dep. Variable:	Т	otal_Output	R-squared	:		0.962		
Model:		OLS	Adj. R-sa	uared:	0.962			
Method:	Le	ast Squares	F-statist	ic:		3828. 0.00		
Date:	Sun,	14 Apr 2024	Prob (F-s	tatistic):				
Time:		15:26:01	Log-Likel		-6794.1			
No. Observatio	ns:	760	AIC:		1.	1.360e+04		
Df Residuals:		754	BIC:		1.	363e+04		
Df Model:		5						
Covariance Typ	e:	nonrobust						
=========	coef	std err	t	P> t	[0.025	0.975		
const	-927.7405	171.363	-5.414	0.000	-1264.145	-591.33		
JCB_Count	271.9102	8.427	32.267	0.000	255.367	288.45		
HDD_Count	361.1449	6.803	53.082	0.000	347.789	374.50		
Poclain_Count	228.4512	27.589	8.280	0.000	174.290	282.61		
Scope_km	-0.3843	0.081	-4.771	0.000	-0.542	-0.22		
Month	9.1140	19.805	0.460	0.646	-29.766	47.99		
Omnibus:		148.154	 Durbin-Wa	tson:		0.745		
Prob(Omnibus):		0.000	Jarque-Be	ra (JB):	479.465			
Skew:		0.924	Prob(JB):		7.	68e-105		
Kurtosis:		6.424	Cond. No.		6.66e+03			

Metrics

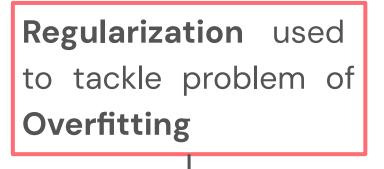
R2 Score shows **Overfitting**: 0.962 (Train) | 0.478 (Test)

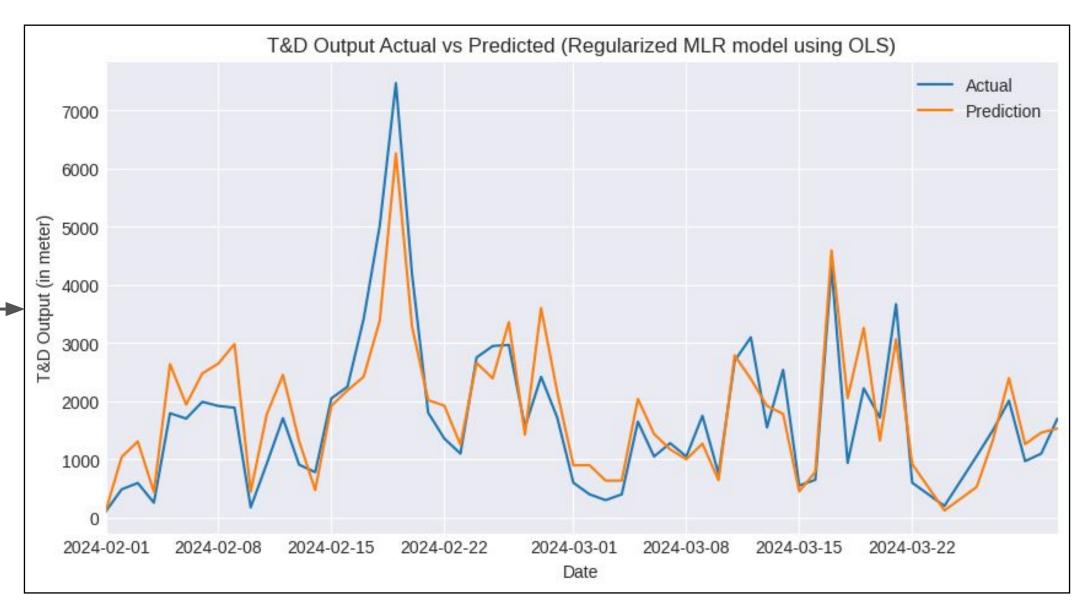
Percentage Difference:

44.53%

- Accurately predicts the Spikes and Dips
- Does not consider the Month variable, hence the **Seasonality Effect**

Linear Regression: Regularized MLR OLS with α = 10





Metrics

R2 Score shows Good Fit: 0.958 (Train) | 0.807 (Test)

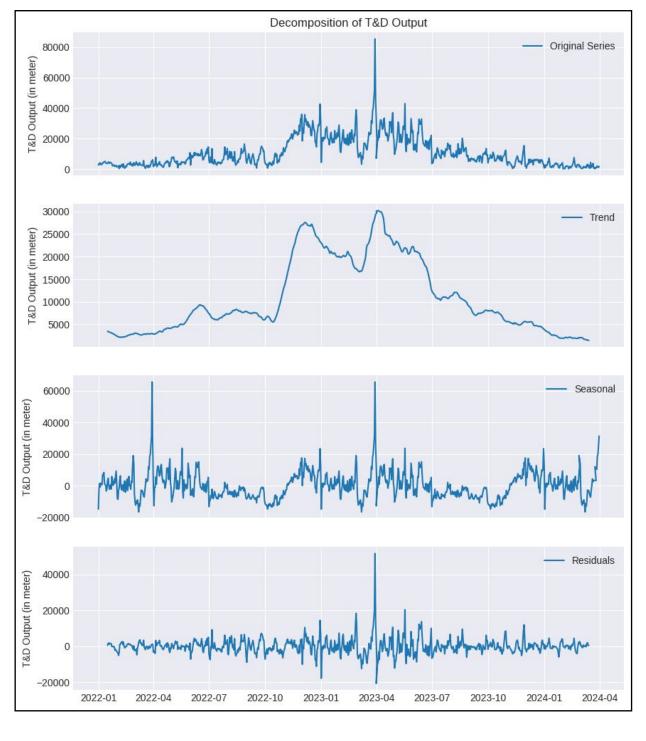
Percentage Difference:

- Statistically, much better than MLR OLS
- Yet still does not consider the Seasonality Effect

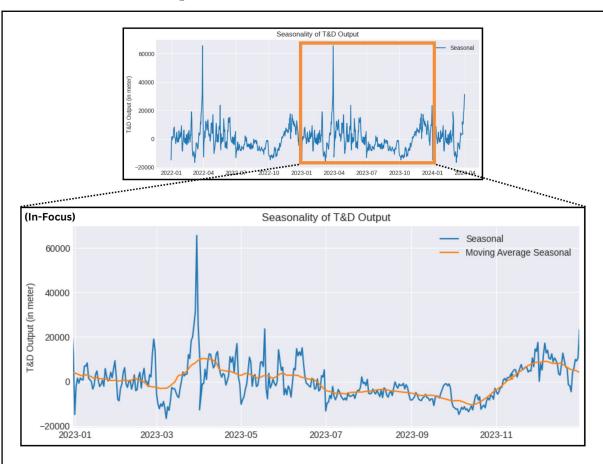
6.3%

Time Series Analysis

Seasonal Decomposition



Seasonality (In-focus)

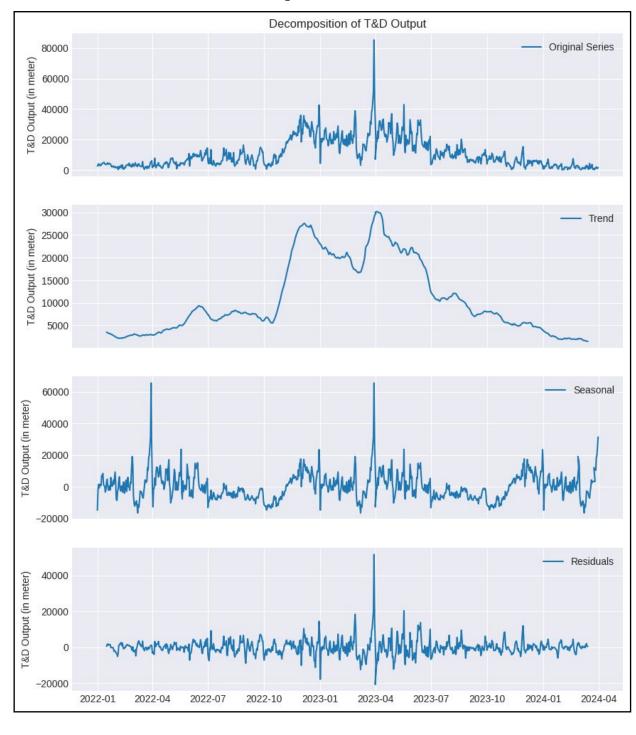


30-day Moving Average shows:

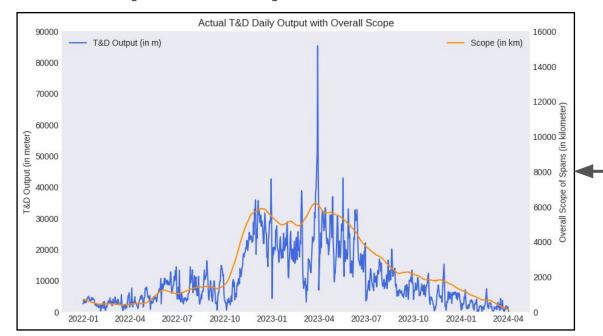
- Peak in April
- Overall High Productivity till June
- Fall till October (Monsoon + Festive)
- Increase till December
- Slight downfall till March

Time Series Analysis

Seasonal Decomposition



Trend (In-focus)



T&D Output as Percentage of Scope

1.5

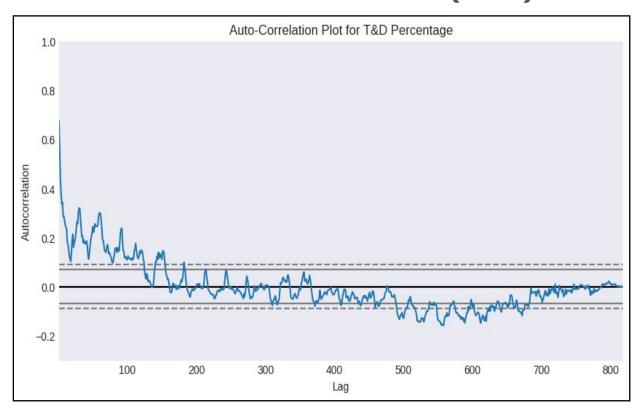
98 90 1.0

2022-01 2022-04 2022-07 2022-10 2023-01 2023-07 2023-10 2024-04

- Upward Shock in October 2022;
 multiple deals signed in MP and Orissa
- Taper-down post-June 2023;
 STL wanted to prevent backorders and finish pending commitments
- Strong Correlation of T&D with Scope: 83.8%
- Use T&D as Percentage of Scope (T&D Percentage) as the new target variable
- T&D Percentage exhibits stationarity; positive for time-series forecasting
- Mathematically backed by the Augmented Dickey-Fuller Test:
 Test-statistic = −5.6; p-value = 8.296×10⁻⁵; supports Stationarity

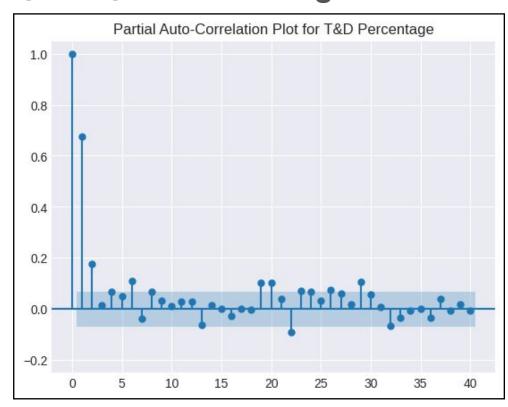
Time Series Analysis

Auto-Correlation Function (ACF) Plot



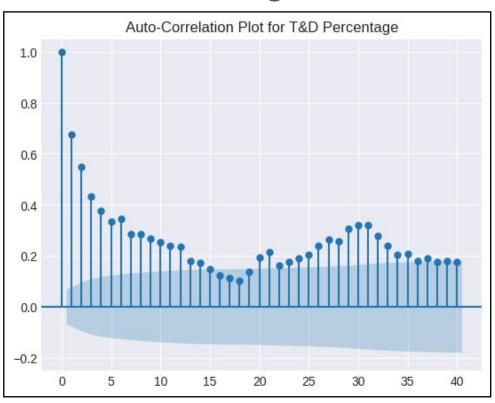
Cyclical nature → SARIMAX over ARIMAX

Partial Auto-Correlation Function (PACF) Plot - 40 Lags



First 3 lags are out of the significance limit → Upper Limit for Auto Regressive (AR) parameter 'p'

ACF Plot - 40 Lags

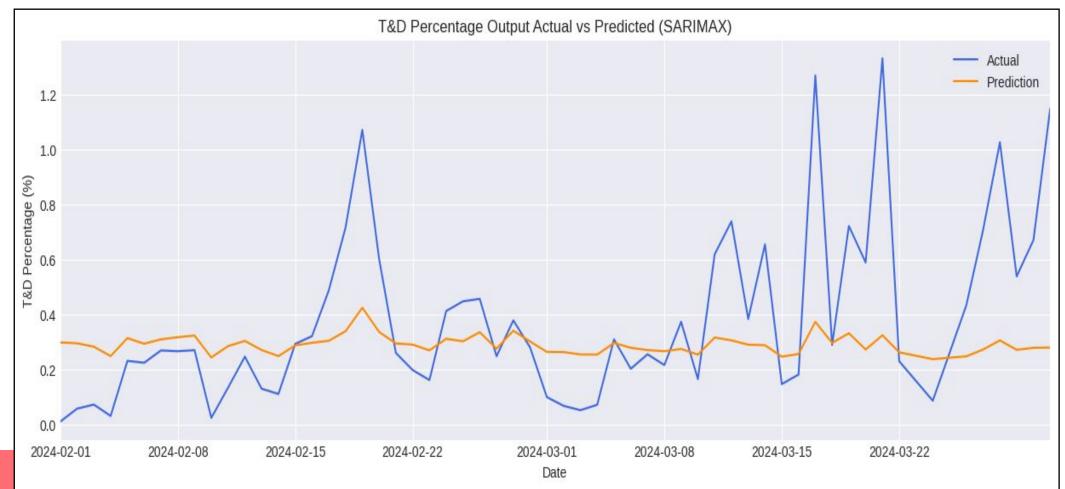


First 15 lags are significant →
Upper Limit for Moving
Average (MA) parameter 'q'

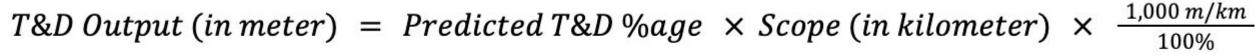
Training an Pyramid-ARIMA Auto-ARIMA model with upper limits

SARIMAX(3,1,1)x(1,0,[],30)

Time Series Analysis: SARIMAX



Dep. Variable: Model:	SARTMAY	(3 1 1)v(TND_%age 1, 0, [], 30)			760 469,523			
Date:	SARTIVA		, 15 Apr 2024		CIIIIOOG		-921.045		
Time:			08:24:15	BIC			-879.35		
Sample:	0 HQIC								
			- 760						
Covariance Type:			opg						
=============	coef	std err	Z	P> z	[0.025	0.975]			
JCB Count	0.0083	0.001	11.000	0.000	0.007	0.010			
Poclain_Count	0.0041	0.003	1.523	0.128	-0.001	0.009			
HDD_Count	0.0093	0.001	9.527	0.000	0.007	0.011			
ar.L1	0.4646	0.041	11.394	0.000	0.385	0.544			
ar.L2	0.0858	0.027	3.191	0.001	0.033	0.139			
ar.L3	-0.0750	0.026	-2.829	0.005	-0.127	-0.023			
ma.L1	-0.8595	0.035	-24.518	0.000	-0.928	-0.791			
ar.S.L30	0.0157	0.025	0.627	0.531	-0.033	0.065			
sigma2	0.0169	0.000	37.799	0.000	0.016	0.018			
Ljung-Box (L1) (Q):			0.56 Jarque	-Bera (JB	: :	1990.82			
Prob(Q):			0.46 Prob(JB): 0					
Heteroskedasticity (H):			0.10 Skew:			-0.23			
Prob(H) (two-sided):			0.00 Kurtos	is:		10.92			





Percentage Difference: 8.44%

- Exogenous Variable: Machine Count
- No peaks but floats around the mean
- Not as accurate as Regularised MLR OLS
- Yet considers the **Seasonality Effect**

Results and Findings

Model Comparison



- Regularised MLR OLS and SARIMAX perform well
- MLR model obtains better accuracy
- SARIMAX model considers the seasonality aspect
- MLR model tends to Over-estimate
- SARIMAX model tends to Under-estimate

Over-Estimation:

- Misallocation of Resources
- Recruit more than necessary
- Added Costs
 - Store-keeping; Extra salaries
- Capital tied-up in inventory
- Idle Capacity due to Over Utilization of Resources
- Stressful Working Environment

Under-Estimation:

- Inefficient allocation of Resources
- Recruit less men and machines
- Inability to meet deadlines
- **Delays** in final HOTO
- Customer Dissatisfaction
- Added Costs
 - Premium Pricing at short-notice



Results and Findings



Model Comparison

Ensemble Model



- Combine the results of Regularised MLR OLS and SARIMAX
- Reduces the Over and Under-Estimation
- Percentage Difference: 1.07%
- Mr. Singh and Mr. Kumar were pleased with the results
- STL is testing the model for final deployment

Results and Findings



Model Comparison

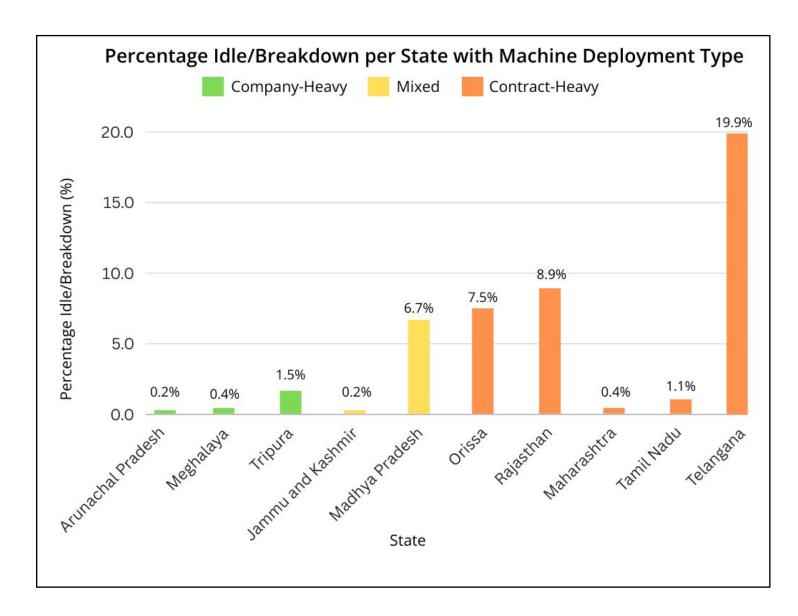


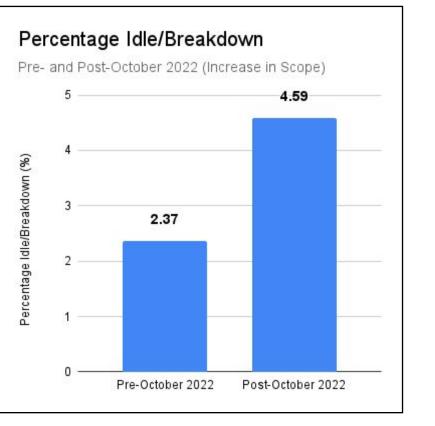
Ensemble Model

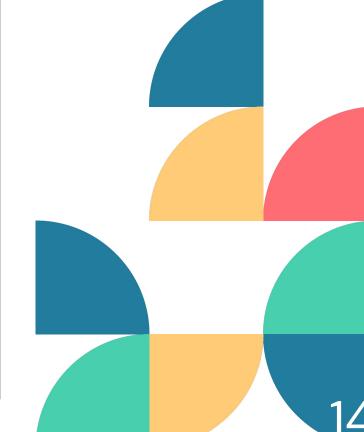




- 80% of machines contracted; 20% company-owned
- Contract-heavy states tend to fall under the trap of over-utilization due to machine burnout
- Periods of High output immediately followed by periods of Low output → Erratic T&D Trendlines
 - Suggests overuse of labour and capital
 - 2x increase in Percentage Idle/Breakdown after signing the MP and Orissa Deals in October 2022







Recommendations

Forecasting Model and Data Improvement Strategies

- Ensemble Model delivers high accuracy
- Robust: Properties of both Linear Regression and Time Series Analysis
- Model can be tweaked for weekly,
 monthly or quarterly prediction
- Model is easy to incrementally retrain for more data
- More localised data (for e.g., soil conditions, climatic conditions, local authorities) could be captured

Prevent Over-Utilization of Equipment

- Current manual capacity planning overestimates the target
- Conduct more vocational training regarding machine breaks and failure
- Monitor machine usage either manually (field engineers) or automatically (sensors)
- Establish a fixed work schedule
- Enforce maximum operating hours (about 10 hrs/day)
- Dedicate shifts for timely equipment maintenance





Thank You!

Links:

- Access Related Resources (Project Reports, Project Poster, Recorded Discussions):
 - Google Drive: https://drive.google.com/drive/folders/1XEISqxikWTlhyDnVc45CHc4o4lp_Pued?usp=sharing
 - O GitHub: https://github.com/Archit-Handa/Optic-Fiber-Deployment-Prediction-Model
- Contact Me:
 - Archit Handa | UG Student BS in Data Science and Applications, IIT Madras
 - o Email: archit20handa@gmail.com | LinkedIn: linkedin.com/in/archit-handa | GitHub: github.com/Archit-Handa
 - O My Resume/CV: https://drive.google.com/file/d/1qNNr9vAACO7qvYVpD8zHfLU D TMBUEu/view?usp=sharing