Cash Flow Predictions Using Prophet

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Abstract: Cash flow forecasting (CFF) is a critical process in the construction industry with significant implications on project viability and financial stability, the efficiency of Artificial Intelligence (AI) in cash flow forecasting for construction projects, comparing the conventional S-Curve method to the AI-based Facebook Prophet model. The research highlighted the growing promise of AI models like neural networks and time-series forecasting methods in improving forecast accuracy, dealing with intricate data, and facilitating proactive decision-making. The approach was to gather cash flow data from an actual residential project in Navi Mumbai. Two models were created: the Prophet model, which is reputed to manage non-linear trends, seasonality, and outliers, and the conventional S-Curve model, which graphs cumulative cash flows against time on the basis of project activity. The Prophet model was implemented with Python libraries Pandas, NumPy, and Matplotlib for data handling and plotting. It was assessed the forecast performance utilizing Root Mean Squared Error (MAE), Mean Absolute Error (MAE), and R-squared (R²). The Prophet model had excellent accuracy, Mean Absolute Error (MAE) with a Normalized value of 1.88 %, Root Mean Square Error (RMSE) with a Normalized value of 5.8%, and R-squared (R²) with a value of 0.9996 indicating high precision. In comparison to the S-Curve, it cut down forecasting time by 98% and provided better precision in cash flow forecasting in different construction elements. The model also needed less human intervention and was more responsive to updates of real-time data. The research shows that forecasting through AI, specifically with the application of Prophet, has massive advantages over standard forecasting methods with respect to precision, effectiveness, and time gains.

Keywords: Prophet, Time-Series Forecasting, AI, S-curve

1. Introduction

In the construction industry, cash flow has been recognized as a serious issue that adversely affects the performance of contracting organizations for decades El-Abbasy et al. (2020). Cash flow forecasting (CFF) is an important process for the construction sector, forecasting cash outflow and inflow from the contractor's point of view to ascertain the net cash flow profile Odeyinka et al. (2012). Conventional methods of forecasting using historical information and expert opinion may be labor-intensive and subject to errors. Artificial intelligence (AI) has come forth as a useful method for enhancing forecasting accuracy and efficiency. A CFF model is important for economic sustainability because it can avoid supply chain delays and ensure a consistent cash flow.

Ineffective cash flow management can result in project delay, cost escalation, or abandonment, With the advancement of technology, Artificial Intelligence (AI) is being increasingly utilized to forecast and optimize cash flows. Financial and budgetary factors are the leading causes of business failure Arditi et al. (2000). More than 60% of contractor failures are due to financial reasons Russell (1991). 77-95% of contractor failures are due to a lack of financing.

AI can improve construction project forecasting by considering historical data, uncovering patterns and relationships that human analysts are not aware of real-time optimizations and precise cash flow forecasts often offer useful information to decision-makers so that they can optimize resource utilization and make effective investment decisions. Without blending finance and scheduling for the project, there are possible cash flow and non-execute schedules issues leading to increased failure rates in contractors. Financings difficulties could impact projects relationships as well as cash flows. More conflicts, claims reporting, and contracting failures are among possible consequences Arditi and Pattanakitchamroon (2008).

To sum up the primary objectives of this research are to develop an AI-based forecasting model that can predict future cash outflows, To Compare time and cost effectiveness of traditional cash flow forecasting methods with AI-driven approaches in construction projects, to develop and apply AI-based models for predicting cash outflows in ongoing construction projects.

2. Literature Review

Cash flow management is a critical aspect of construction projects, significantly impacting profitability and project success. Traditional forecasting techniques such as Earned Value Management (EVM), historical data analysis, and cost-schedule integration have long been used to predict cash flows. However, these methods often struggle to capture real-time complexities in construction projects, leading to inaccuracies in financial planning Cheng et al. (2015).

Cheng et al. (2020) introduced the Symbiotic Organism Search-Optimized Deep Learning Technique (SOS-NN-LSTM), which significantly improved cash flow forecasting accuracy compared to traditional models. Their research demonstrated that AI-based forecasting methods outperformed conventional approaches, reducing forecasting errors by at least 13.4%. Similarly, Mirahadi and Zayed (2016) proposed a Neural-Network-Driven Fuzzy Reasoning (NNDFR) model optimized using Genetic Algorithms (GA)

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International Journal of Scientific Engineering and Research (IJSER) ISSN (Online): 2347-3878 SJIF (2024): 6.623

to estimate construction productivity and predict cash flows. The model demonstrated a 52% improvement in Mean Squared Error (MSE) compared to conventional forecasting methods.

Alavipour and Arditi (2018) highlighted the importance of integrating financing and scheduling to minimize financial risks. Their model optimized project financing costs by analyzing various financing alternatives and automating the cash flow forecasting process.

Weytjens et al. (2019) compared LSTM and Prophet models with traditional ARIMA forecasting techniques, demonstrating that AI-based methods provided superior accuracy in cash flow predictions. Prophet, an open-source forecasting model developed by Facebook (Meta), is particularly effective in business settings with periodic seasonal influences and trend shifts. The model integrates changepoint detection and seasonal variation adjustments to improve forecasting precision (Cheng et al., 2020).

In another study, Liang et al. (2021) introduced a Case-Based Reasoning (CBR) model to forecast construction expenditure cash flow in transportation projects. Their findings highlighted the importance of external market factors and project-specific data in improving forecasting accuracy.

Boomen et al. (2020) emphasized that traditional cost estimation models often underestimate financial risks by ignoring price fluctuations. Their study introduced the Geometric Brownian Motion (GBM) approach to incorporate price uncertainty into cash flow forecasting. Furthermore, Badakhshan et al. (2020) explored the use of System Dynamics (SD) simulation to model supply chain cash flow, revealing how cash flow volatility can impact project sustainability.

3. Research Methodology

3.1 Data Collection

In this research, data collection was crucial in formulating a precise cash flow forecasting model for construction projects. The data set was compiled from an actual construction project "Malhar 24 East" carried out by Malhar Developers, where the contractor was NA Constructions, Sanpada, Navi Mumbai.

3.1.1 Project Specific Details

This entailed critical project parameters as shown below in Figure 1 like the overall area (180,000 sq. ft.), units (144), project duration (36 months), construction cost per sq. ft (₹1360), and total cost of the project (₹24.5 crore). These figures were key to getting to know the cost level and timing of the project, affecting the cash flow profiles directly.



Figure 1: Project Specific Details.

3.1.2 Cash Flow Data

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Table 1: Cash Inflow (Cash Inflow (Opto last Slab)				
В	Podium Area (1,30,713 SQFT			
	(a) 1360/-) = 17,77,69,680/-	1		
	1,30,713	1360	177769680	
Sr. No	Description	%	Amount	
1	FOOTING	5	8888484	
2	PLINTH	5	8888484	
3	Underground Water Tank	2	3555393.6	
4	5TH FLOOR SLAB	2	3555393.6	
5	6th FLOOR SLAB	2	3555393.6	
6	7th FLOOR SLAB	2	3555393.6	
7	8th FLOOR SLAB	2	3555393.6	
8	9th FLOOR SLAB	2	3555393.6	
9	10th FLOOR SLAB	2	3555393.6	
10	11th FLOOR SLAB	2	3555393.6	
11	12th FLOOR SLAB	2	3555393.6	
12	13th FLOOR SLAB	2	3555393.6	
13	14th FLOOR SLAB	2	3555393.6	
14	15th FLOOR SLAB	2	3555393.6	
15	16th FLOOR SLAB	2	3555393.6	
16	17th FLOOR SLAB	2	3555393.6	
17	18th FLOOR SLAB	2	3555393.6	
18	19th FLOOR SLAB	2	3555393.6	
19	20th FLOOR SLAB	2	3555393.6	
20	21st FLOOR SLAB	2	3555393.6	
21	22nd FLOOR SLAB	2	3555393.6	
22	23rd FLOOR SLAB	2	3555393.6	
23	24th FLOOR SLAB	2	3555393.6	
24	25th FLOOR SLAB	2	3555393.6	
25	26th FLOOR SLAB	2	3555393.6	
26	27th FLOOR SLAB	2	3555393.6	
27	28th FLOOR SLAB	2	3555393.6	
	O.H Water Tank and Lift	İ		
28	Machine Room	2	3555393.6	
20	COMPOUND WALL, GATE			
29	AND PCC WORK.	3	5333090.4	
30	AAC BLOCK WORK	12	21332361.6	
31	INTERNAL PLASTER	8	14221574.4	
32	EXTERNAL PLASTER	15	26665452	
	TOTAL	100	177769680	
L				

Cash Inflows as shown above in Table 1 and below in Table 2 represents Information pertaining to percentage-wise payments received by the clients on various construction milestones were listed in tabulated structures.

International Journal of Scientific Engineering and Research (IJSER) ISSN (Online): 2347-3878 SJIF (2024): 6.623

Table 2: Cash Inflow (Upto 4th PT slab)			
٨	Podium Area (50,786 SQFT @		
A	1360/-) = 6,90,68,960/-		
	50,786	1360	69068960
Sr. No	Description	%	Amount
1	ADVANCE	10	6906896
2	FOUNDATION AND PLINTH	20	13813792
3	GROUND FLOOR SLAB	10	6906896
4	1ST FLOOR SLAB	10	6906896
5	2ND FLOOR SLAB	10	6906896
6	3RD FLOOR SLAB	10	6906896
7	4TH FLOOR SLAB	10	6906896
8	RCC WALL (PARDI)	5	3453448
9	Plaster (External & Internal)	15	10360344
	TOTAL	100	69068960

Cash Outflows as shown below in Table 3 represents Monthly data on expenditure regarding construction activities like labor, procurement of materials, payment to subcontractors, hiring of equipment, and miscellaneous was collected in a systematic manner.

Table 3 : Monthly	/ Cash Ou	ıtflows	from	Contractor

S. NO	DESCRIPTION	QTY	RATE	Previous Amt	AMOUNT
1	CEMENT (Bags)	16410	320	5097600.00	5251200.00
2	STEEL (M.T.) 200 MT	1,151.134		66839949.00	66839949.00
3	B/ WIRE (kg)	12486.3	75	936472.50	936472.50
4	CRUSHER SAND	200.76	3200	642432.00	642432.00
5	R/ SAND (Bags)	23575	115	2386135.00	2711125.00
6	R/ SAND (Brass)	5.49	6000	32940.00	32940.00
7	Wash Sand (Brass)	66.83	4500	300735.00	300735.00
8	METAL 1 & 2	231.72	2800	648816.00	648816.00
9	STONE (Brass)	154.11	1800	277398.00	277398.00
10	BRICK- 4" (Nos)	3500	7	24500.00	24500.00
11	BRICK-6" (Nos)	8040	14	112560.00	112560.00
12	WATER (Construction)	983	1100	1081300.00	1081300.00
13	WATER (Drinking)	566	50	28300.00	28300.00
14	NAILS (Kg)	6830	85	580550.00	580550.00
15	Earth Excavation			3500000.00	3500000.00
16	CAC Chemical	4	17500	70000.00	70000.00
17	CARPENTER (Nagendra)	1; s,ab		12276926.00	12600003.00
18	FITTER			7453852.00	7453852.00
19	Labour/Supervisor/Engineer	214080		8514433.00	8728513.00
20	CIDCO WATER	12669		252449.00	252449.00
21	CENTERING MATERIAL	9900		5711195.00	5721095.00
22	MSEDCO LTD	147190		2111200.00	2258390.00
23	RMC	7015		42062147.00	42770462.00
24	Cornice	5050	28	246400.00	246400.00
25	Glass Fibre 125 grm 600	1760	93	163680.00	163680.00
26	Covering Block	20000		230426.00	230426.00
27	EPCO KP 200+ Plastogrip	3016	125	377000.00	377000.00
28	Kamlesh Fabrication			150000.00	150000.00
29	OTHER Exps Motor Light, Wire, Bura Tempo			3000000.00	300000.00
30	M.S.Challan & M.S. Angle	60922		660922.00	660922.00
31	Office Salary, E/Bill, Maintenance, Property Tax, Exps			1300000.00	1350000.00
32	Monopol, T50, Krishna			54770.00	54770.00
33	PT Slab			2445146.00	2445146.00
34	Monopol, Grouting Labour			58000.00	58000.00
35	AAC Block 6"	1979.862	4017.90	7615603.55	7954887.53
36	AAC Block 9"	254.302	4017.90	1021760.01	1021365.72
37	Joint Mortar 40Kg	2190	330	723817.00	723817.00
38	MS Props MSSpan			835400	857080
39	Crane Jumping	35872		155872	155872
40	Crane Oil & Greasing			16500.00	16500.00
41	Govind Construction			2423638.00	2423638.00
42	M.S. Plate	13.63	69140	942378.20	942378.20
43	Crane			4960000.00	4960000.00
44	M.S. Pipe	10	1060	10600.00	10600.00
45	Steel Tube pipe	20	1020	20400.00	20400.00
46	Lift			2700000.00	2700000.00
47	Brickwork Plaster			8778450.00	9168450.00
	Grand Total			199339971.26	202121437.24

Volume 13 Issue 6, June 2025

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3.2 Prophet Model

3.2.1 What is Prophet Model?

Prophet is an open-source time series forecasting software developed by Facebook (now Meta) in 2017. It's particularly geared towards business analysts and data scientists who must forecast data without the need for in-depth knowledge of time series modeling.

Prophet is especially effective in business settings, where:

- There are periodic seasonal influences (weekly, monthly, yearly cycles).
- There is an obvious trend, which might shift over time (e.g., sales acceleration or deceleration).
- You would like to account for holidays or events (Black Friday, national holidays, etc.).
- You want to automatically identify changepoints, where trends suddenly change (e.g., after the launch of a product).



Figure 2: Prophet Framework

Prophet models the time series as an additive model, that is, the sum of various components is shown below in Equation 1

where:

- 1) g(t): Trend function to fit non-periodic time changes.
- s(t): seasonality function to capture periodic changes (daily, weekly, yearly).
- 3) h(t): Holiday impacts, including special events.

 $y(t) = g(t) + s(t) + h(t) + \varepsilon t$

 et: Error term, capturing any random noise not explained by the model.

3.2.3 Prophet Dashboard

An interactive dashboard was created as shown in Figure 3 which utilizes Streamlit for facilitating real-time cash flow projection for construction projects in accordance with the methodology laid out in the study. The dashboard, known as "Construction Cash Flow Forecasting with Prophet", enables uploading historical cash flow data in the form of Excel (.xlsx), up to a maximum file size of 200MB, thus allowing for accommodating large datasets that are common in construction projects. The dashboard first shows a message asking users to upload a valid Excel file if no file is uploaded, providing proper input validation and helping users in an efficient manner. Also, this dashboard takes input from user about basic project information such as project name, location, client name and contractor name which is displayed in the output excel file. This method eases

complicated forecasting processes, decreasing reliance on coding abilities, and enables construction managers and financial planners to see forecasts and make proper decisions about managing cash flow. The app, created with Visual Studio Code and Python 3.8.2.

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12		Al Booknarks
Project Information Project Name:	Construction Cash Flow Forecasting with Prophet	sepay :
Project Location:	Crotery Med Lafer Clone (CANY CON Update), Dentations Data and dop file here Emit 2000 per file = CLI Brown	efiles
Client Name.	🖬 Overall Prophet Model Performance Across All Descriptions	
Contractor Name:	No predictions available. Please upload a valid Excel file and ensure the data is connect.	

Figure 3 : Dashboard Interface

3.2 S-Curve

S-curve is a logistic growth curve that has widespread application in construction project management to project cumulative cash flow vs time the formula for Calculating S-Curve is shown below in Equation 2.

$$(t) = \frac{B}{1 + e^{-k(t - t_0)}}$$
(2)

Where:

(1)

Υ

- Y(t) is the Cumulative cash outflow at time t
- B is the budget ceiling (Total Project Cost)
- k is the growth rate parameter
- to is the inflection point (time at which the growth rate is maximum)
- e is Euler's number.

3.3 Software's and Libraries

Data Collection and Preprocessing Libraries:	Normalization and Feature Engineering Libraries:	
• Pandas: Used for reading, manipulating, and cleaning large datasets.	• Scikit-learn: Used for splitting datasets, Provides tools for scaling and preprocessing data.	
NumPy: Handles numerical operations, including normalization and mathematical calculations.	 re: The re module offers regular expression matching operations 	
Software:	Visual Studio de.	
Programmin Pytho	ng language: n 3.8	
Model Development & Validation Tools:	Build an Interactive Dashboard:	
Prophet: It's is an open-source library for time series forecasting that can automatically account for seasonality, holidays, and missing data. RMSE, MAE, R-Squared it provides Model Validation Score	 Streamlit: It's an efficient and easy solution for building data science and machine learning web apps. Matplotlib/Seaborn: Used for data visualization to identify trends and outliers 	

Figure 4 : Software's & Libraries

From the above Figure 4 it shows different types of Libraries used in code such as Pandas, NumPy, Scikit-learn, and re are used for data preprocessing and collection libraries are crucial for dealing with big data. Pandas is responsible for numerical operations, and NumPy is responsible for normalization and mathematical computations. Regular Expressions assists with text data processing and cleaning. Prophet is a time series forecasting library, responsible for seasonality, holidays, and missing data. Scikit-learn evaluation metrics (RMSE, MAE, R²) are utilized to confirm

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model predictions. Streamlit makes it easy to build interactive web-based dashboards for machine learning and data science projects. Matplotlib is employed to visualize predicted vs actual values and predict trends.

4. Result & Discussion

4.1 Model Evaluation Metrics

- 1) Absolute Metrics
 - RMSE: 148,437.02
 - MAE: 48,446.84
 - R²: 0.9996
- 2) Normalized Metrics (as % of Mean Actual Values)
 Normalized RMSE: 5.80%
 - Normalized MAE: 1.88%



Figure 5: Actual vs Forecasted Values of Grand Total using Prophet

Here above the Figure 5 shows the comparison between actual and projected cash flows with Prophet model during the period from March 2022 until March 2025. Months are on the x-axis and cumulative cash flow value, that is in crores, up to 2.5 units on the y-axis. Red dots show the actual cash outflows faced by the contractor, whereas blue dotted line shows the projected values obtained from the model. This is one of a larger group of graphics presented here there are 48 more such graphs, which shows the model's performance on individual items like AAC blocks, cement, steel, labour, equipment, and utilities.



Figure 6: Cash Flow Forecasting of Grand Total by S-Curve

The curve's gradual slope replicates the trend of progressive expenditure common in building: gradual outflow in the initial stages, sharp outflows at the time of peak building, and reducing towards project completion. The x-axis illustrates the project timeline ranging from March 2022 to February 2025, and the y-axis shows the overall outflow of funds in Indian Rupees (INR) in steps up to ₹25 crores as shown in Figure 6. Cash outgoings during the first six months (2022–03 to 2022–08) are kept low, following the initial stage of construction work in which excavation, site levelling, and mobilization take place. A steeper increase later in 2022 and up to early 2023 can be seen as an indication of the procurement of material such as cement, steel, and AAC blocks, alongside rising labour work. The cash outflow remains steadily into 2024 with minimal fluctuation that might reflect variations in the monthly progress of work, vendor payment cycles, or payments made at milestones.

4.2 Cost & Time Comparison



Figure 7: Cash Outflow Comparison

Table 3: Time Comparison	between	Prophet and	S-Curve
Me	ethod		

Method	Process Steps	Time Taken (For This Dataset)
	Manual data collection	
	& entry (1208 records)	
	Spreadsheet modeling	3-4 working days (24-32 hours)
Traditional S-Curve	(S-Curve generation)	for complete forecasting of this
induction of our to	Manual updates for	dataset
	progress changes	Galaset
	Review & approval	
	cycle	
	Data preprocessing (automated)	
	Prophet model training	15-30 Mins for the same dataset
Prophet AI Model	& forecasting	(including preprocessing and
-	(automated)	forecast generation)
	Visualization (automated in Streamlit)	

5. Conclusions

The research delves into the application of Artificial Intelligence (AI) methods, in this case, Prophet model for cash flow forecasting in construction projects. Conventional methods of forecasting, based on manual analysis of data and past trends, are not capable of dealing with the

Volume 13 Issue 6, June 2025 <u>www.ijser.in</u> Licensed Under Creative Commons Attribution CC BY complexity, uncertainty, and dynamic behavior of cash flows in construction. AI models provide a major advantage as they are able to process vast amounts of data, discover concealed patterns, and make more precise predictions. The methodology entailed a systematic method, gathering historical data from a running construction project, and training and testing Prophet models for its capacity to accommodate seasonality, trend shifts, and outliers. The Prophet model was tested by applying common performance measures like Mean Absolute Error (MAE) with a Normalized value of 1.88 %, Root Mean Square Error (RMSE) with a Normalized value of 5.8%, and R-squared (R^2) with a value of 0.9996. The findings illustrated that the AI-based method decreases time by 98 % in Comparison with S-Curve Method and reduces human effort, errors and aids construction companies in staying financially healthy throughout a project cycle.

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