TRC2101

Update of the ARDOT Workforce Forecasting System

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Arkansas Department of Transportation

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16. Abstract

This report assesses the existing manpower forecasting tool used for workforce allocation and provides a comprehensive description of the development of a new, modern forecasting system. An extensive review of existing tools and state-of-the-art methods for similar forecasting was conducted, including the identification of key factors influencing manpower forecast planning. Historical data were retrieved and analyzed to better understand past workforce requirements, and regression models were developed based on this data. Distribution models were created to estimate workforce utilization over the lifespan of projects and by the job types available in the data. Specialized regression models were developed using work types and grouping similar work types for insufficient project listings, and a methodology for forecasting was integrated into the backend of a web application. Extract, Transform, Load (ETL) capabilities were implemented within the software system, and a user-friendly front-end application was developed to ensure smooth access for users. Recommendations are made to monitor key factors established to influence the workforce on projects for future system improvements. Additionally, it is recommended that more data be made available to the system to enable the possibility of more advanced models, which current data limitations hinder.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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List of Abbreviations and Acronyms

API	Application Programming Interface
ARDOT	Arkansas Department of Transportation
Caltrans	California Department of Transportation
CEI	Consultant Engineering and Inspection
CPI	Consumer Price Index
CPM	Critical Path Method
DOT	Department of Transportation
HR	Human Resource
MIDOT	Michigan Department of Transportation
NCDOT	North Carolina Department of Transportation
NCHRP	National Cooperative Highway Research Program
NDDOT	North Dakota Department of Transportation
RE	Resident Engineer
SCDOT	South Carolina Department of Transportation
STA	State Transportation Agency
TSC	Transportation Service Center
TxDOT	Texas Department of Transportation
UDOT	Utah Department of Transportation
USDOT	United States Department of Transportation
VDOT	Virginia Department of Transportation

Executive Summary

The TRC2101 research project, funded by the Arkansas Department of Transportation (ARDOT) and conducted by the University of Arkansas, Fayetteville, aimed to modernize the existing manpower forecasting tool by transforming it into an automated software solution. This update enhances forecasting accuracy, supporting more effective workforce planning. The project involved extensive research to refine forecasting models, develop a robust workflow, and implement the solution using modern tools and programming techniques. The outcome is a web-based application, accessible via browsers, with the capability to integrate seamlessly with ARDOT's existing databases.

To identify the most effective forecasting techniques, an extensive literature review was conducted. This included a detailed analysis of existing software, forecasting methods used by DOTs across the United States, and cutting-edge techniques being adopted in the industry. This review led to the development of a comprehensive set of alternative forecasting approaches and offered valuable insights into key factors that influence workforce requirements for ARDOT project completion. To advance model development, a data request was made, and the provided data were thoroughly analyzed to gain insights from ARDOT's historical project completion records. Notable findings included shifts in job descriptions over time, which were standardized and consistently mapped for further analysis.

Further analysis of the data highlighted the effectiveness of regression models in forecasting total man-hour requirements. A cleaning and filtering procedure was developed to standardize the processing of historical data, ensuring that new data undergoes the same treatment. A workflow was also established to separate specialized regression models based on work type. Additionally, job distribution techniques, using historical distribution ratios, were adopted to allocate man-hours across forecasted projects over the required timelines. Due to the varying project lengths across groups and work types, specialized mathematical models were developed to handle the distribution of man-hours for projects with differing durations. The final man-hour requirements were adjusted using historical data to determine the total staff count, which is ARDOT's preferred unit of measurement. The R-squared values of the regression models used for man-hour estimation ranged from 0.526 to 0.918, with the default model for unclassified projects achieving an R-squared value of up to 0.808.

The forecasting tool was built with robust architecture, ensuring both efficiency and scalability. Designed to be hosted on ARDOT's servers, the tool is accessible via any modern web browser and supports multi-user access. The back-end is developed in C# and uses a MySQL database to handle its data needs. It is also designed to stream data directly from ARDOT databases, particularly planning information and historical data essential for forecasting. The forecasting models were integrated into the system's development framework, enabling the generation of updated models when new historical data is provided for forecasting purposes.

The front-end of the tool, named CURSOR, was developed using React.js, providing a dynamic and responsive user interface. Several other modern tools were also used in design and development to ensure seamless and intuitive usability for the end-users. For security, Microsoft Azure AD was implemented, ensuring that only authorized users can access the system. The tool allows generated results to be exported in both PDF and XLSX formats, facilitating easy further processing of the forecasted estimates.

Overall, CURSOR is a valuable upgrade from the existing forecasting tool. With its improved interface and automated features, it is designed for ease of use by forecasting engineers and other users, significantly reducing the time spent on forecasting tasks. Its high prediction accuracy ensures better workforce planning for the agency, helping to avoid the costs associated with over- or under-hiring for future projects.

Chapter 1. Project Overview

Structure of the Report

Following the Project Overview in Chapter 1, this report is organized as follows:

- Chapter 2 reviews the existing workforce forecasting software and state-of-the-practice forecasting models.
- Chapter 3 describes the data collection and cleaning process.
- Chapter 4 presents the development of the workforce forecasting models.
- Chapter 5 summarizes the development of the workforce forecasting tool.
- Chapter 6 describes the key findings, addresses limitations, and includes suggestions for future work.

Background

By the end of the first decade of the 21st century, state-managed lane miles had increased beyond 4 percent. Over the same period, full-time equivalent staff had decreased by almost 10 percent (Taylor et al. 2013). This trend clearly indicates a lack of adequate manpower to efficiently manage highway infrastructure. Roles such as inspectors, surveyors, engineers, and managers are essential for all highway construction and maintenance projects to ensure that contractors provide the necessary quality and quantity to meet plans and specifications. A shortfall in available personnel for these roles can potentially lead to delays in project completion, cost overruns, and reduced project quality. Conversely, overstaffing can also be detrimental, negatively impacting project performance, wasting scarce human resources, and misaligning funds. The responsibility for ensuring adequate construction staffing levels to meet the state's construction needs lies with the Department of Transportation (DOTs), who are also tasked with forecasting future construction personnel staffing levels.

Adequate construction staffing is critical to the cost, schedule, quality, and safety of highway construction projects. However, the variable nature of construction project volume, project type, location, and scale can complicate estimating staffing requirements for both short- and long-term planning. While accurate planning and forecasting of construction personnel is crucial for maintaining and improving the nation's roadway infrastructure, there is a lack of widespread use of formal construction staff forecasting methods across DOTs. This does not imply that DOTs are not performing construction staffing analyses; rather, construction workforce forecasting may be conducted informally or periodically, rather than being integrated into regular planning activities.

NCHRP Synthesis 450: Forecasting Highway Construction Staffing Requirements found that of 40 DOTs that responded to requests for information, only seven reported having some formal method or tool for estimating construction staffing needs for future projects (Taylor et al. 2013). These methods and tools varied in approach, ranging from simple construction staffing heuristics based on project type to complex forecasting models developed through multivariate regression analysis of historic project data, considering seasonal fluctuations in staffing requirements. For example, the construction staff forecasting system used at the Michigan DOT (MIDOT) operates in Microsoft Excel with defined cells for user inputs and other protected cells that calculate total staffing needs. The Texas DOT (TxDOT) has regression models developed by the University of Texas that use project type and cost to forecast engineering-design labor hours (Persad et al. 1995). The South Carolina DOT (SCDOT) employs similar regression models to predict construction project administration staffing requirements based on project type and employee classification (Bell and Brandenburg 2003). Conversely, the Virginia DOT (VDOT) develops construction staff forecasts periodically by having each district calculate the number of construction personnel required based on the projects funded in each fiscal year, considering type, location, duration, and dollar value of the project. Taylor et al. (2013) reported that the methods described above may be outdated, raising questions about the accuracy of the forecasts produced by these methods. For instance, ARDOT's forecasting tool was developed in the 1970s and is not equipped to reflect today's workforce productivity and the agency's changing resource usage patterns. Many existing tools and methods used by state DOTs, as described in the literature, lack validation efforts necessary to verify the accuracy of their methodologies. As state DOTs continue to manage larger infrastructure systems with fewer employees, the need for accurate estimates of construction staffing personnel becomes critical for controlling project budgets and quality.

Recognizing this need, NCHRP Research Report 923: Workforce Optimization Workbook for Transportation Construction Projects provides state transportation agencies with guidance to identify their construction staffing needs and allocate their state or consultant engineering and inspection staff and consultant resources to highway construction projects (Taylor et al. 2020). The guidance outlines 35 specific staffing strategies that may help alleviate construction staff challenges. These strategies are linked by work type and staffing function to assist agency personnel in selecting specific strategies. The electronic version of the Workforce Optimization Workbook (e-WOW) allows users to input project information and automatically calculate staffing needs while highlighting strategies to alleviate staffing challenges. While this guidance and tool are not tailored to individual DOTs' needs and characteristics, they provide a framework for creating such resources and can serve as a secondary reference for workforce forecasts made from state-specific data.

Benefits of the Study

Accurate forecasting of construction staff over the short and long term can lead to overall cost benefits for ARDOT. To monetize the benefits of the proposed project, we adopted the following approach. First, we determined the number of man-power hours for each highway project planned for 2019. The project list was gathered from ARDOT's Statewide Transportation Improvement Program 2019–2022 Report (ARDOT 2018). Man-power hours were estimated based on project cost, following the procedures outlined in a study for the TxDOT, "Assessment of Staffing Needs for Construction Inspection" (Kim et al. 2016). We assigned each 2019 ARDOT project to a project category in the TxDOT study. Next, we estimated the potential monetary benefits of improved workforce estimation for two hypothetical scenarios.

In Scenario 1, we consider that ARDOT's existing forecasting method, "The Manpower Forecasting System Formulas Program", overestimates the man-hour requirement by 15 percent, while the proposed method will reduce error by 10 percent, meaning the new model overestimates by only 5 percent. For Scenario 1, we assume an average cost per man-hour for construction projects of $45 (Wilmot et al., 1999), and that overestimation of man-power hours results in added project costs (e.g., the number of extra man-hours not needed multiplied by the assumed hourly wage rate for in-house personnel). (See Table 2)

In Scenario 2, we assume the ARDOT model underestimates the man-hour requirement by 15 percent, while the proposed model reduces error by 10 percent, meaning the new model underestimates by only 5 percent. For Scenario 2, we assume an average cost per man-hour for construction projects of $54, which is the cost of necessary consultant labor to compensate for unplanned man-hours (Wilmot et al., 1999). Alternatively, we could have assumed that unplanned man-hours would be compensated by overtime estimated at $67.50, as per the ARDOT Personnel Manual. However, we chose the more conservative (lower) estimate for consultant labor. Underestimation results in added project costs (e.g., the number of extra man-hours needed multiplied by the assumed hourly wage rate for consultant personnel). (See Table 3)

The total project cost considers the budget of this proposed project ($120K or $0.120 Million). Total benefits for each scenario are calculated as the difference between costs associated with over- or underestimation using the current ARDOT estimation model and the proposed improved model. Cost-Benefit (B/C) ratios of 31.25 and 40.58 result for Scenarios 1 (Overestimation) and 2 (Underestimation), respectively (Table 1).

Table 1. Summary of B/C Ratios for Two Scenarios

Scenarios	Total Benefit from the Developed Model	Total Cost of the Project	B/C Ratio
Scenario 1: Overestimation	$3.75 Million	$0.120 Million	31.25
Scenario 2: Underestimation	$4.87 Million	$0.120 Million	40.58

Table 2. Estimated Benefit of Proposed Project for Scenario 1 – Overestimation of Man-Power Requirements

(1) Project Type	(2) No. of Projects	(3) Estimated Project Cost (M $	(4) Man-Hours per Project (hr/M $)	(5) Total Man-Hour	(6) Number of Man-Hours Overestimated-Existing Model, 15%	(7) Number of Man-Hours Overestimated - Proposed Model, 5%	(8) Cost/ Man-Hour	(9) Additional Costs Due to Overestimation ($) - Existing Model	(10) Additional Costs Due to Overestimation ($) - Proposed Model	(11) Estimated Benefits ($)
Bridge Replacement	55	100.4	1172	117,681	17,652	5884	$45	794,345	264,782	529,563
Widen Freeway	15	447.9	635	284,450	42,667	14,222	$45	1,920,037	640,012	1,280,024
Miscellaneous Construction	11	63.1	1322	83,352	12,503	4168	$45	562,623	187,541	375,082
Rehab. of Existing Road	11	59.4	921	54,666	8200	2733	$45	368,996	122,999	245,997
Restoration	8	115.4	991	114,351	17,153	5718	$45	771,869	257,290	514,579
Safety	8	59.3	1496	88,727	13,309	4436	$45	598,908	199,636	399,272
Widen Non-Freeway	3	23.9	941	22,481	3372	1124	$45	151,745	50,582	101,163
Landscape/Scenic	2	9.4	1603	15,067	2260	753	$45	101,700	33,900	67,800

Enhance.										
Bridge Widening or Rehab	1	3.9	990	3862	579	193	$45	26,071	8690	17,381
Interchange New or Reconstructed	1	14.0	765	10,705	1606	535	$45	72,261	24,087	48,174
New Location Freeway	1	4.5	537	2414	362	121	$45	16,297	5432	10,865
New Location Non-Freeway	1	25.0	694	17,342	2601	867	$45	117,061	39,020	78,041
Upgrade to Standard Freeway	1	20.0	915	18,293	2744	915	$45	123,475	41,158	82,317
Total Projects in 2019 with State Funds	**118**	**946**	**12982**	**833,391**	**125,008**	**41,669**	**$45**	**5,625,388**	**1,875,129**	**3,750,258**

Notes:

1. Columns (1), (2), and (3) are derived from ARDOT STIP (2019–2022); categories from the TxDOT (Kim et al. 2016) study are applied.
2. Column (4) is derived from Kim et al. (2016); it includes (i) project supervision, (ii) inspection of work in progress and project records, (iii) job control (includes testing), (iv) construction surveys (post-letting), (v) design verification, changes, and alterations, (vi) preparation of as-built plans, and (vii) other charges.
3. Column (5) is calculated by multiplying Column (3) by Column (4).
4. Column (6) is calculated by multiplying the manpower estimate in Column (5) by 15 percent.
5. Column (7) is calculated by multiplying the manpower estimate in Column (5) by 5 percent.
6. Column (8) is derived from Wilmot et al. (1999).
7. Columns (9) and (10). are calculated by multiplying Columns (6) and (7) by the assumed hourly rate of $45, respectively.
8. Column (11) is calculated as the difference between Columns (9) and (10).

Table 3. Estimated Benefit of Proposed Project for Scenario 2 – Underestimation of Man-Power Requirements

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Project Type	**No. of Projects**	**Estimated Project Cost (M $)**	**Man-hours per Project (hr./M $)**	**Total Man-Hou**	**Number of Man-Hours Underestimated - Existing Model, 15%**	**Number of Man-Hours Underestimated - Proposed Model, 5%**	**Cost/Man-hour**	**Additional Costs Due to Underestimation ($) -Existing Model**	**Additional Costs Due to Underestimation ($) -Proposed Model**	**Estimated Benefits ($)**
Bridge Replacement	55	100.4	1172	117,681	17,652	5884	$54	953,214	264,782	688,432
Widen Freeway	15	447.9	635	284,450	42,667	14,222	$54	2,304,044	640,012	1,664,032
Miscellaneous Construction	11	63.1	1322	83,352	12,503	4168	$54	675,148	187,541	487,607
Rehab. of Existing Road	11	59.4	921	54,666	8200	2733	$54	442,795	122,999	319,797
Restoration	8	115.4	991	114,351	17,153	5718	$54	926,242	257,290	668,953
Safety	8	59.3	1496	88,727	13,309	4436	$54	718,689	199,636	519,053
Widen Non-Freeway	3	23.9	941	22,481	3372	1124	$54	182,094	50,582	131,512
Landscape/Scenic Enhance.	2	9.4	1603	15,067	2260	753	$54	122,039	33,900	88,140
Bridge Widening or Rehab	1	3.9	990	3862	579	193	$54	31,285	8690	22,595
Interchange New or Reconstructed	1	14.0	765	10,705	1606	535	$54	86,714	24,087	62,627
New Location Freeway	1	4.5	537	2414	362	121	$54	19,556	5432	14,124
New Location Non-Freeway	1	25.0	694	17,342	2601	867	$54	140,473	39,020	101,453
Upgrade to Standard Freeway	1	20.0	915	18,293	2744	915	$54	148,171	41,158	107,012
Total Projects in 2019 with State Funds	**118**	**$946**	**12982**	**833,391**	**125,008**	**41,669**	**$54**	**6,750,464**	**1,875,129**	**4,875,335**

Notes:

1. All calculations as in Table 1.
2. Column (8) is derived from Wilmot et al. (1999) for consultant labor.

Project Objectives

The central objective of the project was to develop a more accurate forecasting tool to predict construction staff requirements for ARDOT's highway construction projects. The research had the following supporting objectives:

Objective 1: Comprehensive Review of Practice

The research team reviewed existing studies and practices to: (a) identify the most accurate and state-of-the-art forecasting methods and (b) understand the working principles of the outdated forecasting tool currently in use by ARDOT. Forecasting techniques used across DOTs—such as TxDOT, MIDOT, and SCDOT—were explored. Workforce forecasting efforts for construction engineers, such as the e-WOW, were also considered, and best practices were adopted. Multivariate linear regression was adopted to estimate total workforce requirements for projects, while methods specified in the e-WOW were used for distributing the workforce across job titles.

Objective 2: Methodology for Development of Forecasting Models

The research team applied multivariate linear regression to forecast the level of workforce required by new projects. Models were grouped by similarity in project type, with project types having sufficient projects handled as a single group. The estimated project cost and linear difference in years were considered as independent variables in the model. The cost is expected to be affected by inflation year after year; hence, adjustment factors were included to account for discrepancies. The linear difference in years is also modeled based on the assumption that construction efforts benefit from advancements in technology, thereby influencing workforce requirements. Historical data on projects were obtained from ARDOT, containing relevant information such as employee work hours and project details.

Objective 3: Implementation of Automated Forecasting Tool

The research team developed a web-based application deployed on ARDOT's private server. Developed using C# and multiple front end development tools, the forecasting system incorporates the developed forecasting model and provides a final output of the forecast in easily accessible formats (PDF and Excel). The tool also allows direct user adjustments to estimates, providing flexibility based on engineering judgment. Security cautions were implemented during deployment, ensuring that the tool is safely available to ARDOT employees within the agency network.

Objective 4: Detailed User Manual

A comprehensive user manual with step-by-step instructions on how to use the forecasting tool has been developed. Video examples and tutorials of using the software are provided in the user manual, simplifying its use for first-time users.

Chapter 2. Review of Workforce Forecasting Methods

This chapter reviews state-of-the-practice (DOT forecasts) and state-of-the-art (academic research) methods employed in forecasting construction engineer workforce requirements and other construction workers. A review of the existing forecast tool was also conducted, focusing on the existing user interaction of ARDOT employees with such a tool and exploring its limitations. Decisions on modeling approach and software implementation were made based on the reviewed practices.

Existing Forecasting Tool (AHTD Manpower Forecasting Program)

The existing forecasting tool, AHTD Manpower Forecasting Program, was first developed 50 years ago in the 1970s. Implemented by in-house AHTD engineers at the time, the most recent update to the tool was in 2008. The system requirements for the program include the outdated Windows 3.1, 8MB of RAM, and a meager 20MB of HDD space. Relying on past ARDOT project data, it has generally been used for estimates moderated by experienced engineering judgment. Some of the required inputs for the tool include the cost of the construction project, expected completion date, and the type of facility (rural or urban). Furthermore, the program operates based on categories of the construction work available at that time, some of which are outdated and not observed in recent projects, such as Frontage Road, Study, Utility, Resurface & Shoulder, etc.

Working on the principles of regression analysis, the program outputs the required manpower needed in "person-hours/month". While there was no significant deviation in the required manpower for given projects, the costs of implementing projects have varied significantly, leading to regular updates of the program over the years. Past updates were made to the program in 1992, 1995, and 2008. Predictions for more recent projects, particularly large projects, have also been reported to be erroneous. Additionally, the program does not take advantage of the improved computing power and resources available today. It is limited to the computer running the old operating system that matches the established requirements.

NCHRP Synthesis 450

The NCHRP synthesis presented data gathered from 40 STAs out of the 50 across the country. The report showed an average increase of 4.1 percent in the total lane-miles managed by the STAs during the same period, when there was an average decrease of 9.78 percent in STA personnel. To compensate for inadequate personnel numbers, some agencies have resorted to employing consultant personnel. This statistic justifies the need for adequate workforce planning for the nation's roadway infrastructure system.

The report synthesized factors that influence construction staffing levels in STAs and the systems currently being used to forecast construction project staff. This was carried out by reviewing existing tools used by the agencies for forecasting, in addition to an online survey distributed to all 51 STAs and site visits to the agencies for construction staffing data collection.

Only seven out of the 40 STAs that responded have a formal method or tool for forecasting their staffing needs. The methods adopted for forecasting were diverse, with some approaches being simple construction staffing heuristics based on project type. Other methods were more advanced, employing multivariate regression models and considering seasonal variations in staffing requirements. However, there were no reports on the validation of these forecasting methods.

The study also identified poor specifications, quality plans, and cost estimates as the factors most responsible for increasing staffing requirements for any given project. These factors differed from those increasing staffing requirements for construction engineering and administration, which are influenced by an increase in third-party coordination efforts. Conversely, only a few factors, such as an increase in the experience level of construction inspectors, reduced the number of construction inspection personnel required. Furthermore, 96 percent of respondents asserted the use of consultants to fill staffing needs due to insufficient in-house construction staff. The report further indicated the limited adoption of technology within the agencies.

The report recommends certain characteristics common to the reviewed systems that newly developed systems should consider. One such characteristic is basing the system on the timeline of the forecast. The systems become more complex as the analysis timeline lengthens, often requiring more resources to develop and maintain. Another characteristic is the need for project schedules when estimating staff needs. Most systems have some form of project duration estimation that includes generic type activities. The last characteristic refers to the importance of the relationship between staff requirements and the level of work required. The direct use of historical data or published standards of staffing levels should be approached with caution and consider the specific projects at hand. Relying solely on historical data can be misleading, as it does not account for the provision where selected projects hired more or less staff than needed.

Six out of the surveyed STAs have a formal method of forecasting their staff requirements. Most of these tools are based on Microsoft Excel, with minor differences in implementation among the STAs. These tools are utilized by the Michigan Department of Transportation (MIDOT), North Carolina Department of Transportation (NCDOT), and Utah Department of Transportation (UDOT). The NCDOT has six defined generic project types for all its projects, while MIDOT estimates the level of staff requirements in each Transportation Service Center (TSC, the equivalent of "district offices" in other DOTs). UDOT was also reported to use macros to aggregate the billable hours for technicians and engineers. Other methods, such as estimating manpower needs using planning standards and the bottom-up approach, were also employed by DOTs such as North Dakota Department of Transportation (NDDOT) and California Department of Transportation (Caltrans), respectively. Selected DOTs with comprehensive forecasting approaches, both covered within the NCHRP Synthesis 450 and beyond, are further reviewed below, and readers are directed to the report for a more extensive review of the tools used at the aforementioned DOTs.

Texas Department of Transportation (TxDOT)

NCHRP Synthesis 450 reported on the TxDOT forecasting tool, which was in development at the time. Simple linear regression and multivariate regressions were used to derive the model for forecasting staff requirements (Persad et al. 1995). Figure 1 shows the monthly forecast of TxDOT employees with the average number of staff needed. Two models were developed, with one utilizing the estimated construction cost as the independent variable, while the other included both the construction cost and project type as independent variables. Stepwise regression analysis of the historical data was conducted, with both the construction cost and project type variables proving to be excellent predictors. The final forecasting model has several underlying assumptions which includes the following: A single inspector can handle $250,000 in a month and up to a $5 Million bridge project, beyond which two inspectors will be required; a single inspector is sufficient for seal coat projects estimated to cost $850,000/month and overall projects with estimates below $1,500,000/month; a single manager is sufficient for up to 14 employees; one inspector can handle up to 10 local-let projects; and constant inflation of 5 percent yearly will reduce the effective inspector need at a similar rate, and shared work duties will occur, with some inspectors from other projects assisting during peak periods on an individual project. Furthermore, the forecasting system accounts for variations in geographic locations and seasonality, allocating staff as required.

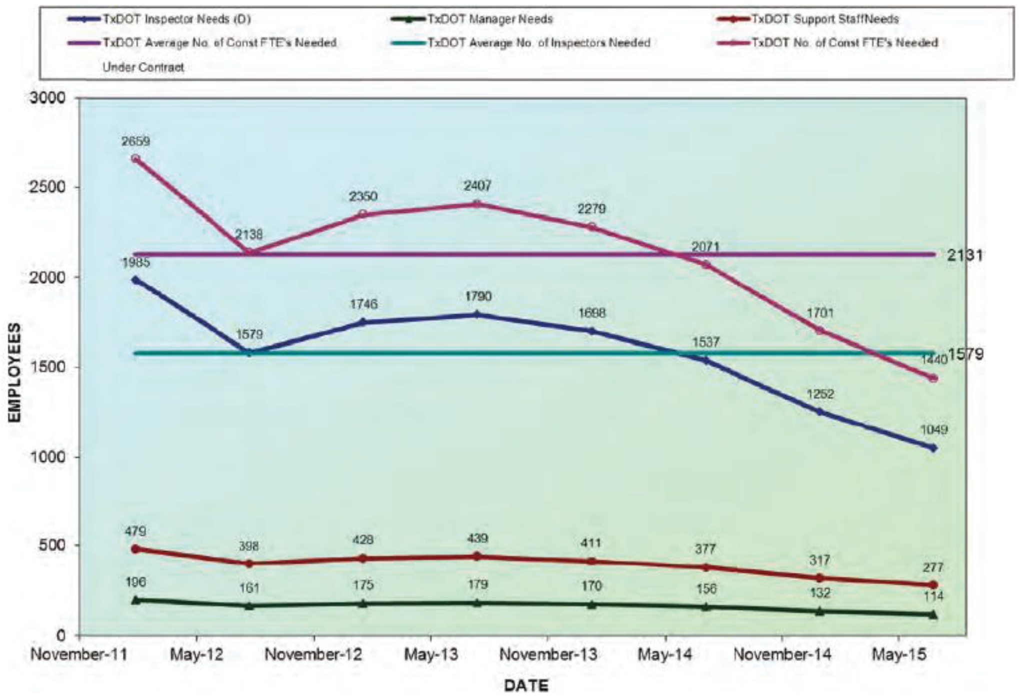


Figure 1. TxDOT Staffing Analysis (Source: NCHRP Synthesis 450)

South Carolina Department of Transportation (SCDOT)

The SCDOT employed a similar approach to TxDOT by developing regression models to forecast its manpower needs. The independent variables considered for regression were the project type and estimated cost for selected employee classifications. The project types investigated included bridges and overpasses, guardrail, pavement marking, rehabilitation, resigning, "grade, drain, base, and resurfacing", signal installation, resurfacing, widening, and "others". The model considered 130 recently completed highway projects at the time of development. Additionally, 11,000 employee payroll entries were used to generate manpower requirements over the selected projects. A log-log relationship was employed in the regression analysis, yielding satisfactory results. An investigation into the differences in the geographic location of the projects showed no obvious differences; hence, all projects were considered without regard to location differences. In addition, the manpower requirement for each project is further distributed to the appropriate employee classifications based on typical task allocation percentages estimated from questionnaire data. The generated data from this distribution are further used in conjunction with critical path method (CPM) scheduling processes to facilitate planning and manpower resource leveling. The employee classifications considered in the tool include resident engineers, asphalt plant inspectors, asphalt road inspectors, earthwork inspectors, concrete inspectors, foundation inspectors, and survey crewmembers. The final regression model for the DOT is presented in Figure 2.

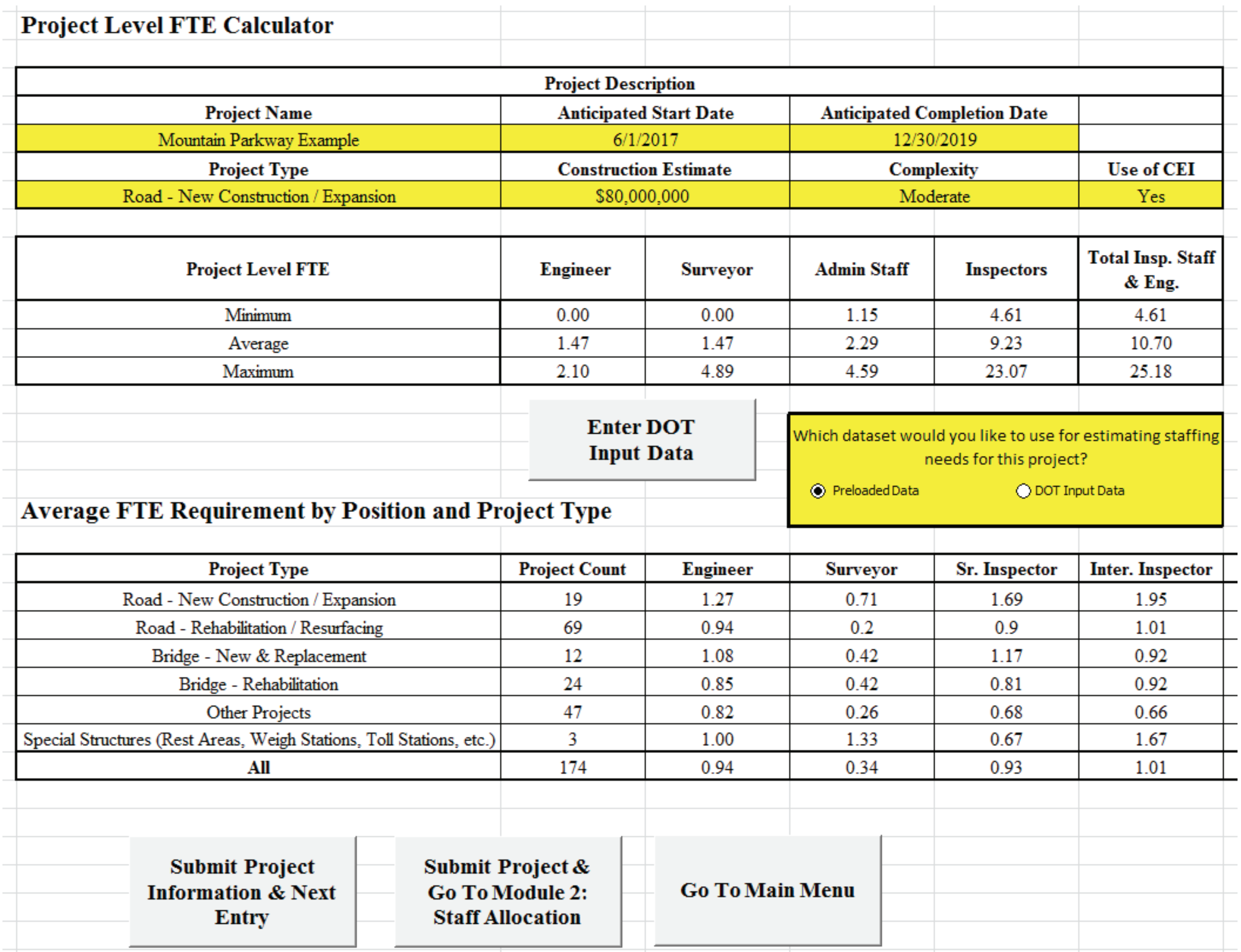
Project category	Equation	R^2	N (number of data points)
All Categories	$y = 0.2773x^{0.6318}$	0.3752	134
Bridges and Approaches	$y = 3.2455x^{0.468}$	0.2488	32
Grading, Drainage, Base, and Resurfacing	$y = 0.1233x^{0.6926}$	0.4877	15
Guard Rail	—	—	2
Pavement Markings	$y = 1.7659x^{0.4753}$	0.0887	18
Rehabilitation	—	—	1
Resigning	—	—	1
Resurfacing	$y = 1.057x^{0.5319}$	0.2774	40
Signalization	$y = 29.261x^{0.2336}$	0.1028	8
Widening	$y = 8E-07x^{1.4574}$	0.2335	5
Other	$y = 0.0038x^{0.9503}$	0.7392	12

Figure 2. SCDOT Regression Models (Bell, 2003)

NCHRP Project 20-107

The NCHRP Project 20-107 aimed to develop guidance for construction staffing levels to assist STAs in better managing highway construction projects, resulting in the e-WOW, an electronic Workforce Optimization Workbook. The project employed staff forecasting methods (10 states), staffing strategy case studies (7 states), project survey results (305 projects across 16 states), literature review, and a guidance validation workshop (22 participants from 14 states). The guidance tool recommends staffing levels based on project type, risk projections, and FTE-consultant mix, providing strategies for planning staff allocations at the district and project levels, as well as strategies to help alleviate construction staff challenges.

The e-WOW is an electronic version of the Workforce Optimization Workbook, an output of the NCHRP Project 20-107, designed to be user-friendly and help users optimize the information provided by the Workbook. The e-WOW was developed on a Microsoft Excel Macro-Enabled Worksheet (.xlsm) and is designed for use on PC only, as Macintosh users may encounter difficulties using the program. A screenshot of the workbook is shown in Figure 3.



Project Level FTE Calculator

Project Description			
Project Name	**Anticipated Start Date**	**Anticipated Completion Date**	
Mountain Parkway Example	6/1/2017	12/30/2019	
Project Type	**Construction Estimate**	**Complexity**	**Use of CEI**
Road - New Construction / Expansion	$80,000,000	Moderate	Yes

Project Level FTE	Engineer	Surveyor	Admin Staff	Inspectors	Total Insp. Staff & Eng.
Minimum	0.00	0.00	1.15	4.61	4.61
Average	1.47	1.47	2.29	9.23	10.70
Maximum	2.10	4.89	4.59	23.07	25.18

Average FTE Requirement by Position and Project Type

Project Type	Project Count	Engineer	Surveyor	Sr. Inspector	Inter. Inspector
Road - New Construction / Expansion	19	1.27	0.71	1.69	1.95
Road - Rehabilitation / Resurfacing	69	0.94	0.2	0.9	1.01
Bridge - New & Replacement	12	1.08	0.42	1.17	0.92
Bridge - Rehabilitation	24	0.85	0.42	0.81	0.92
Other Projects	47	0.82	0.26	0.68	0.66
Special Structures (Rest Areas, Weigh Stations, Toll Stations, etc.)	3	1.00	1.33	0.67	1.67
All	174	0.94	0.34	0.93	1.01

Figure 3. FTE Calculator with the e-WOW (Source: e-WOW User Guide)

The e-WOW consists of three modules. Module I helps project the level of staffing required at each position, generated on a project-by-project basis and based on the survey data collected. The forecast considers project characteristics such as type, complexity, size, location (rural/urban), use of consultants, and staff's union status. It is important to note that the positions considered in the e-WOW are generic and defined as project engineer, surveyor, inspector, and admin staff. Module II of the workbook focuses on aggregating scheduled projects and estimating month-to-month construction staffing. It can also be used with estimated staffing levels from other sources aside from those estimated by Module I of the e-WOW. It attempts to balance staffing across projects through predefined peak and non-peak periods in the projects. Further adjustments are allowed for prioritization and staffing requirements to create the most appropriate scenario for the portfolio projects. Module III aims to maximize the efficiency of the staffing level based on the risk level of the projects. This final module contains a staffing strategy matrix that provides a framework for decision-making based on user-assigned risks to different work types within the project portfolio. To facilitate estimations in the workbook, Figures 4, 5, and 6, as shown, provide the factors of adjustment integrated into the workflow.

Project Type	Cost Range (Million $)	Resident Engineer			Surveyor			Admin Staff			Inspectors		
		5%	Mean	95%	5%	Mean	95%	5%	Mean	95%	5%	Mean	95%
Road – new construction/ expansion	<5	0.00	0.96	2.00	0.00	0.03	0.25	0.00	0.55	3.00	1.00	1.72	3.00
	5 – 25	1.00	1.20	2.00	0.00	0.75	2.00	0.00	1.18	2.00	2.00	3.90	6.00
	>25	0.00	1.40	2.00	0.00	1.20	4.00	1.00	2.00	4.00	4.00	8.00	20.00
Road – rehabilitation/ resurfacing	<1	0.00	0.79	1.00	0.00	0.17	1.00	0.00	0.53	2.00	0.10	1.57	3.00
	1 – 5	0.00	0.86	1.00	0.00	0.16	1.00	0.00	0.75	2.95	1.00	2.73	5.00
	>5	0.25	1.25	4.25	0.00	0.42	2.75	0.00	0.94	5.25	1.25	4.83	15.00
Bridge – new and replacement	<1	0.00	0.80	1.00	0.00	0.20	1.00	0.00	1.00	2.00	1.00	1.60	3.00
	1 – 10	0.00	0.97	2.00	0.00	0.42	2.00	0.00	0.67	2.00	0.70	2.53	7.00
	>10	1.00	1.38	2.00	0.00	0.63	3.00	0.00	1.13	2.00	1.00	9.13	21.00
Bridge – rehabilitation	<1	0.00	0.92	1.00	0.00	0.00	0.00	0.00	0.52	2.50	1.00	1.29	2.00
	1 – 5	0.00	0.71	1.00	0.00	0.17	4.00	0.00	0.67	1.00	1.00	2.00	5.00
	>5	0.25	1.04	2.00	0.00	0.41	1.00	0.00	0.73	2.00	2.25	4.38	7.00
Other projects	<0.5	0.00	0.82	1.35	0.00	0.22	1.35	0.00	0.68	3.00	1.00	1.41	2.35
	0.5 – 1	0.00	0.85	1.95	0.00	0.16	1.95	0.00	0.63	1.95	0.05	1.57	3.95
	>1	0.00	0.94	2.00	0.00	0.49	2.90	0.00	0.73	3.00	0.00	2.08	4.45

Figure 4. FTE by Project Type and Position (NCHRP Report 923)

	Resident Engineer		Surveyor		Admin Staff		Inspectors	
	Staff Only	With Con-sultants	Staff Only	w/Cons	Staff Only	w/Cons	Staff Only	With Con-sultants
Road – new construction/expansion	0.90	1.08	1.14	0.90	0.76	1.18	0.68	1.23
Road – rehabilitation/resurfacing	0.98	1.06	1.18	0.52	0.83	1.44	0.79	1.56
Bridge – new and replacement	0.92	1.05	0.48	1.37	1.33	0.76	0.85	1.11
Bridge – rehabilitation	0.83	1.10	0.29	1.43	0.91	1.05	1.08	0.95
Other projects	0.90	1.13	1.16	0.78	1.00	1.00	1.05	0.94

Figure 5. Adjustment Factors for Projects Based on CEI Consultants (NCHRP Report 923)

	Resident Engineer	Surveyor	Admin Staff	Inspectors
Noncomplex	0.93	0.55	0.89	0.77
Moderate	0.98	1.36	0.97	0.94
Complex	1.39	2.64	1.54	2.29

Figure 6. Adjustment factors based on Complexity (NCHRP Report 923)

State-Of-The-Art Methods

Following the state-of-the-practice review, the research team evaluated methods used to estimate workforce requirements across the industry, with a particular focus on the construction sector. Specifically, the research team sought state-of-the-art methods to estimate total workforce requirements.

These methods can be broadly classified into qualitative methods and quantitative approaches (Kumar 2009). The quantitative approaches received more consideration and are further classified into regression, time series, labor multiplier, and neural network-based models. These are discussed in greater detail here.

Qualitative Methods

These are some of the simplest methods and are commonly employed when datasets are limited or when high-quality empirical data is nonexistent. Some of the methods used include descriptive statistics, which analyze organizational behavior based on surveys, and discrete-choice experiments, where hypothetical alternatives are presented to participants. The most elaborate and widely used approach is the Delphi method, which relies on several experts to iteratively respond to questionnaires until a consensus is reached. This method has been extensively utilized across various industries and has proven to be an effective alternative when reliable empirical data is lacking. However, critiques of the method include its overreliance on experts, which makes it susceptible to subjective bias, and the time required for multiple expert involvement, which can increase costs. Several improved versions of the Delphi method, such as the Policy Delphi, Goals Delphi, Ranking Delphi, Numerical Delphi, and Normative Delphi, have also been developed to enhance the original version for better estimation (Safarishahrbijari 2018; Kumar 2009).

Quantitative Methods

Quantitative methods are utilized when sufficient empirical data is available for workforce forecasting. These methods generally provide better estimates and are more reliable than qualitative methods, making them the predominant approaches developed for workforce forecasting. These approaches can be further categorized and are discussed in the sections below:

Time Series Models

These methods are popular for forecasting future values based on historical data and have been adopted in various industries. Because of their operational characteristics, they are better suited for large-scale forecasting, such as national and regional forecasts using economic variables. They can also be adopted by STAs, with several studies supporting this regard. Basic time series methods, such as Box-Jenkins ARIMA and exponential smoothing, have been used for construction workforce forecasts. These methods are typically preferred when there is limited knowledge of the properties of the response variable (workforce requirements) since they primarily rely on historical data. They can also adjust for seasonality. Attempts have been made to introduce multivariate inputs into time series models, such as in the case of Vector Error Correction models (Wong et al. 2007). In addition to statistical approaches, other methods formulate the forecasting problem as a time series model, such as the gray model, where the first-order gray model has been proposed for workforce construction forecasts (Ho and Head n.d.). Advanced methods also incorporate deep learning techniques for the forecast, such as Seq2Seq models and LSTM models (Ashtab and Ryoo 2022).

Regression Models

Regression models are based on prior knowledge and theory related to the problem. These models also make provision for the estimation of the effects of different variables on the response variable. Input variables are selected using theoretical knowledge of the problem and are popular for agency-level workforce forecasts in the construction industry. They have been widely adopted within STAs and can be either simple linear regression or multiple linear regression models (Bell and Brandenburg 2003; Persad et al. 1995). They have proven particularly useful in workforce forecasting, especially when there is limited data for more sophisticated models.

Machine Learning Models

Machine learning models are data-intensive and preferred when a large historical dataset is available in the given STA. They are commonly formulated as either time series or regression problems and are sometimes integrated with existing solutions within these categories. An example is the integration of multivariate deep learning using the Seq2Seq model, where the time series problem was formulated, and predictions were made using deep learning techniques (Ashtab and Ryoo 2022). Additionally, integrated machine learning models set up as regression problems have also been proposed. These models utilize variables known through theoretical knowledge of the response variable to influence workforce forecasts. Furthermore, such models require large historical datasets, as most of these models are data-intensive.

Summary of Findings and Recommendations

Based on the literature reviewed, the research team recommends a new forecasting tool based on multivariate regression analysis of historical data. This tool would be developed based on existing project types within ARDOT, as well as the estimated costs of individual future projects. Past studies have demonstrated a strong relationship between these variables and manpower requirements, proving to be the most advanced technique for forecasting on a project-by-project basis. The new system would be a web-based forecasting tool that allows for the inclusion of newly completed projects as the tool matures. The distribution of manpower requirements would be based on e-WOW's distribution; however, this would be expanded to include job classifications from ARDOT that are not considered in e-WOW.

Chapter 3. Forecasting Model Development

This chapter presents the methodology for developing the forecasting models, including data gathering and cleaning, model selection, identification of work type groupings, distribution of forecasted hours by job title, and estimation of monthly workforce requirements.

Data Collection

Two major files were retrieved from ARDOT, containing details about the projects and the workforce needed for these projects. These files include project details data, summarizing information on past awarded projects, and human resource data, which contains the hourly logs of individual engineers and inspectors based on the projects they worked on.

Human Resource Data

The human resource data primarily contains information about employees working on projects at ARDOT. This data includes personal information on each employee, their position at ARDOT, and specifics about the projects they worked on for specific days. The data retrieved were collected from a relatively new system ("Kronos") that ARDOT adopted for human resource (HR) data management. ARDOT provided 10 years of data (2012–2021) in CSV file formats. The fields of the data provided are described in Table 4.

Table 4. Field Descriptions of Historical HR Data

Field Name	Type	Description
Employee Name	Text	Official name of the employee
Job Title Description	Text	Description of the assigned position of the employee
Division	Text	District office description
Date	Date	Date when the time was logged
Sec-RE-crew	Integer	Resident engineer crew number
Activity Name – Level 1	Alphanumeric	Project code under which the job was performed
Actual Activity Hours	Decimal	Number of hours reported for the day
Actual Wage Rate	Decimal	Current wage rate of the employee
Total	Decimal	Total wage for the day

Extensive exploration of the HR data revealed changes in job title descriptions over time. Certain descriptions were absent in later years, while newer descriptions appeared that were absent prior. Further investigation suggests a total shift in job title descriptions in 2017, with subtle changes made before and after this shift. The most recent job title descriptions have remained consistent and are adopted as the primary job titles for consideration.

Identifying the old and new descriptions for job titles is important to ensure all job title data are accounted for. A dictionary mapping old and current job title descriptions was not readily available from ARDOT; hence, trends in the data were used to uncover the name changes. Sudden changes in employee job title descriptions were tracked across the data, and possible changes due to promotion or demotion were identified by examining groups of employees with similar job title description changes. The full job title descriptions used by ARDOT across the years were made available. The final mapping between past and new job title descriptions was presented to ARDOT's correspondence for validation. The mapped job title descriptions were approved for use and are shown in Table 5.

Table 5. Job Classification Title Changes Map

Previous Job Title Descriptions	Present Job Title Descriptions
Resident Engineer	Staff Engineer
Assistant Resident Engineer	Senior Engineer
Advanced Const Field Engineer, Construction Field Engr II, Construction Field Engr I	Advanced Engineer
Construction Project Coord	Construction Project Coordinator
Engineer I, Engineer	Engineer
Senior Inspector, Inspector, Construction Aide III	Construction Inspector
Senior Construction Material Insp, Construction Materials Insp	Construction Materials Inspector
Resident Office Tech	Resident Office Tech
Construction Aide II, Construction Aide I, Guard, Maintenance Aide II, Maintenance Aide I, General Laborer, Construction Helper	Construction Aide
Field Clerk, Office Admin Asst I, Field Clerk I	Field Clerk
Seasonal Employee	Seasonal Employee
Intern, Engineering Student Intern	Intern

Project Data

The “project data” was retrieved from the project management team at ARDOT. The data collected contains all primary details of projects spanning the same 10-year period (2012–2021) as the HR data. The data were provided in Excel format and were divided into two sheets named “Normal Jobs” and “State Aid Jobs”, with both sheets having the same structure. A description of the fields in the data provided is presented in Table 6.

Table 6: Metadata for Project Data Provided

Field Name	Type	Description
Job No	Alphanumeric	Now called “Project No.” It’s a unique code for the project
Type Work	Text	This is the category of work to which the project belongs
Description	Text	This describes the kind of work done on the project
Award Amt	Float	The total amount budgeted for the project
Job Status	Text	Provides the current state of the project (completed or not)
Job Name	Text	A detailed title of the project
Let Year	Date	The year when the project was awarded
Beg Date	Date	The date construction begins on the project
End Date	Date	The final date of construction on the project

A plot of the different work types available in the project data is shown in Figure 7, where projects of type “Resurfacing” occurred more frequently than any other work type. In total, 3910 project details were provided over the given period, spanning 30 project types.

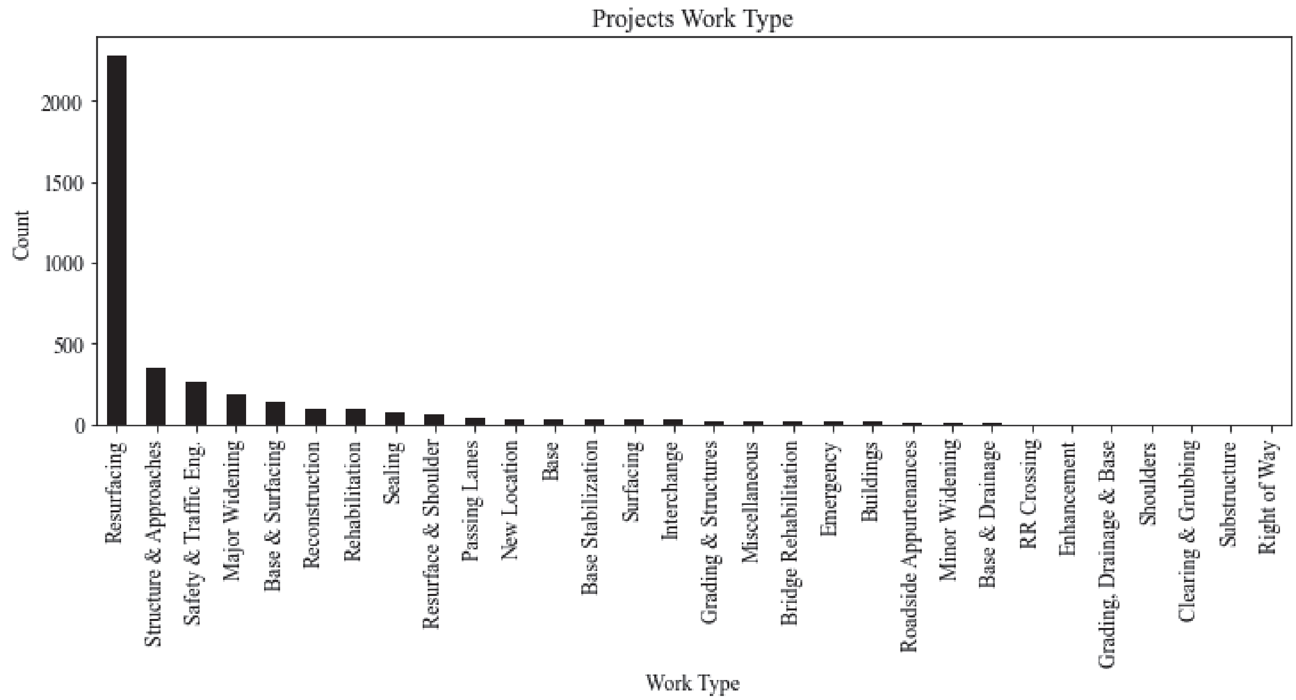


Figure 7. Project Work Type Distribution

The "Project No," formerly known as and labeled as the "Job No," serves as the primary key connecting the HR data with the project data. The project number is labeled as "Activity Level – 1" in the HR data and as "Job No." in the project data, both of which are referred to as the "project number" in this report. The two datasets were merged using the project number for further analysis of the historical data.

Merging Datasets

A quick overview of the project numbers within the two datasets revealed possible inconsistencies in the labeling of the project numbers. Some project numbers exist with a prefix label of "C" or "CC" in one dataset but are absent in the other. This suspicion was confirmed by ARDOT's correspondence, indicating that the prefix signifies "construction". The project numbers were reconciled before merging the two datasets. The total number of projects present after merging totals 2282. Further information was requested on the remaining 1628 projects, and analysis proceeded with the merged data. A visual flowchart on the cleaning of the data is shown in Figure 8.

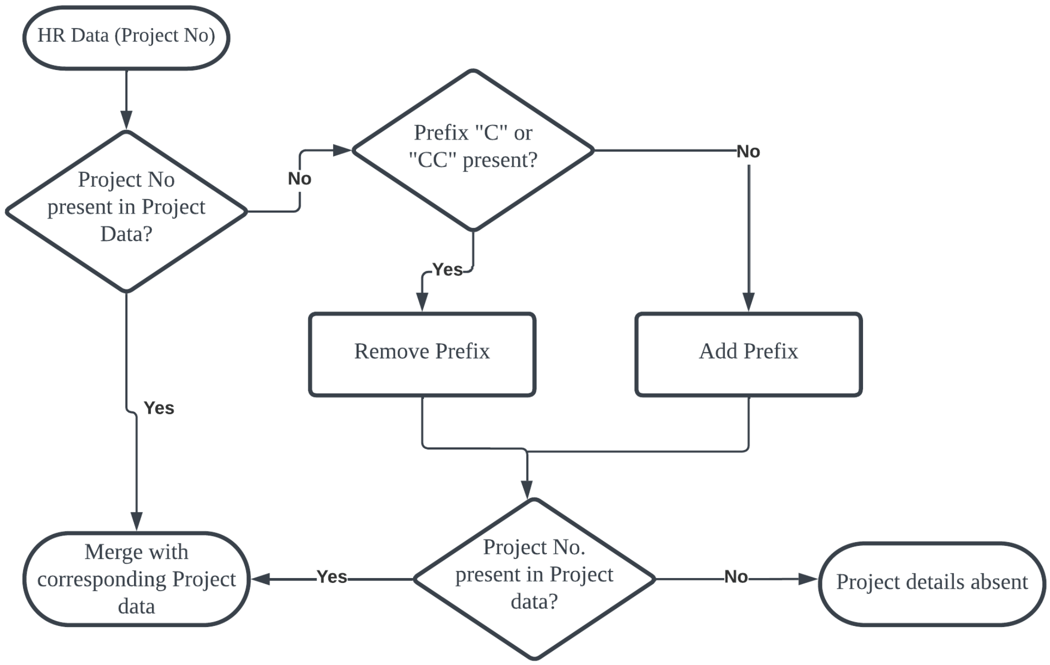


Figure 8. Flowchart for Data Cleaning

Filtering and Selection

The merged dataset contains details of all projects with their corresponding HR information. Only standard completed projects are required to ensure that the data is complete and robust for forecasting. Since the project data contains a field describing the progress of each project, the data were filtered by completion to exclude ongoing projects. A total of 438 ongoing projects were identified and removed, leaving 1844 project data entries.

A quick look into the project data by year revealed that projects constructed in 2012 recorded substantially lower person-hours compared to those of other years. This concern was raised, and the team alerted ARDOT's correspondence regarding the project. The feedback indicated that the 2012 HR data might have flaws since this was the year a new system, "Kronos", was introduced to log employee hours. It was decided to exclude all projects that began in 2012, retaining only data from projects that commenced in 2013. A visual representation of the filtering and selection is presented in Figure 9.

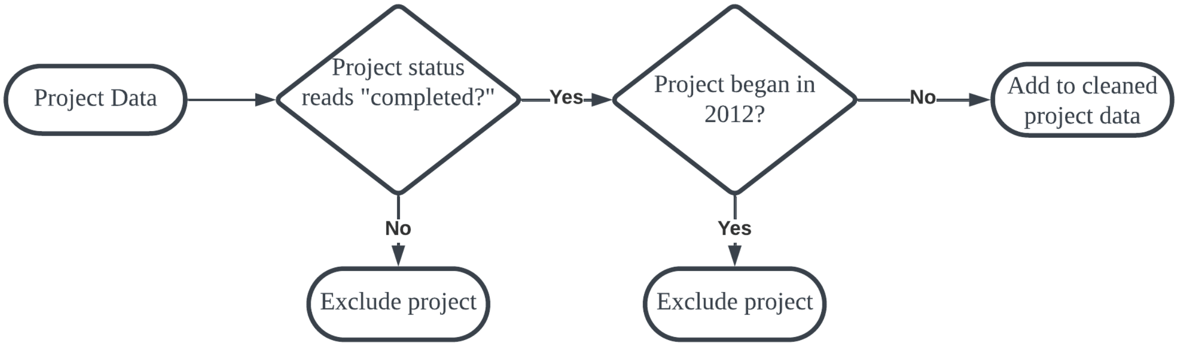


Figure 9. Flowchart for Project Filtering and Selection

Past studies (Bell et al. 2003; Persad et al. 1995) have shown a log-log linear relationship between project costs and the total number of person-hours for given projects. A log-log plot of the costs and person-hours for the historical ARDOT data is shown in Figure 10. This clearly illustrates the deviation of specific projects. (Bell et al., 2003) noted in the South Carolina historical data that projects where CEI consultants were employed recorded significantly fewer person-hours. However, there was no information on the use of CEI for the projects retrieved from ARDOT; hence, these significantly lower person-hours were used to identify such projects. Two methods were tested for this: one involved excluding projects with person--hour records below a certain threshold, while the second method excluded projects based on the ratio of the project cost to person-hours. The second method was favored, as it did not risk excluding actual small projects that would normally require fewer person-hours to implement. Consequently, projects with a cost-to-person-hour ratio below the 95th percentile were excluded as they likely employed CEI consultants, supplementing the efforts of the ARDOT engineers and leading to fewer hours being recorded compared to projects with similar attributes.

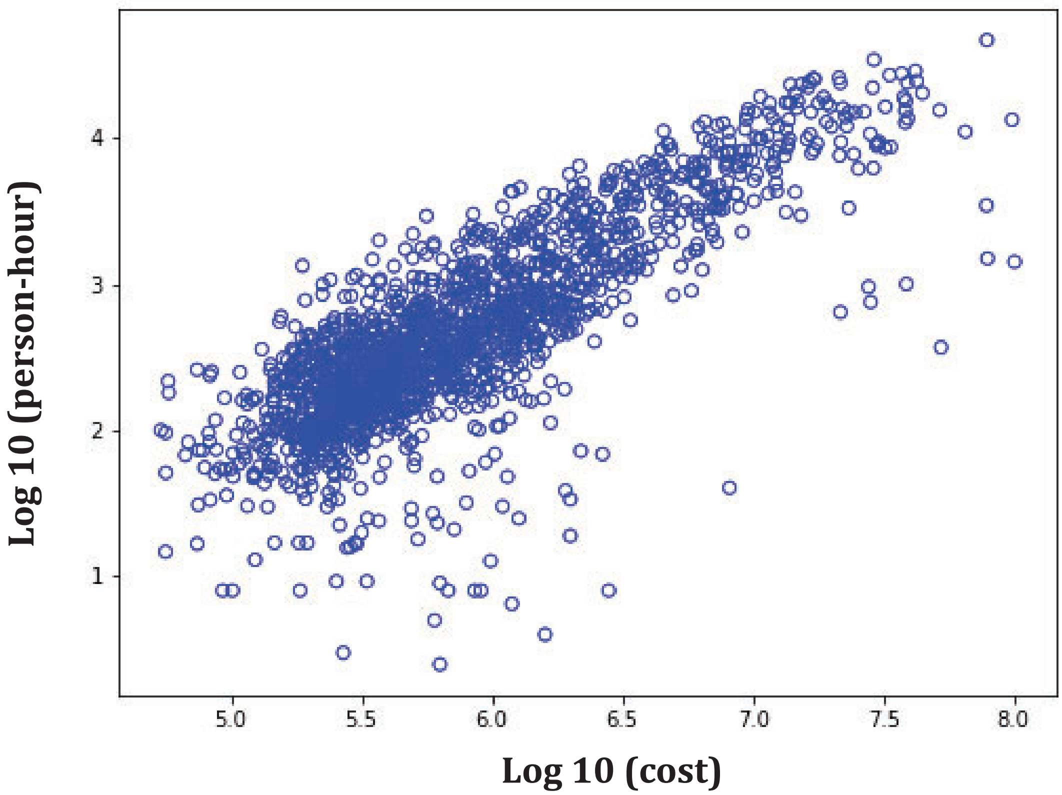


Figure 10. Log-Log Plot Relationship Between Cost and Person-Hour

One major drawback identified by the previous AHTD forecasting software was the changing relationship between project costs over the years. While insignificant within a short period, inflation in item prices is inherently transferred to project costs over time. To address this, price inflation over time is considered when adjusting the assigned costs of projects that span several years to a common base year. This ensures a consistent relationship between cost and the level of manpower required, regardless of the period for which the project budget was estimated. A database expected to be updated yearly was proposed to track yearly inflation through the CPI (Consumer Price Index). The earliest year of the projects within the database was observed to be 2011. This was chosen as the base year to which all other project costs are adjusted. The adjusted cost for any project within a given year is estimated using Equation 1, as described.

$$Cost_{base\_year} = Cost_{current\_year} \times \frac{CPI_{base\_year}}{CPI_{current\_year}}$$

Equation 1: Adjusted Cost for Any Project

Factors Influencing Workforce Forecasting

Several factors identified in the literature have been found to influence workforce dynamics in projects. Only a few of these factors were available in the retrieved dataset and were subsequently utilized as the project progressed. Some of the identified factors are discussed further in this section.

Cost

This is one of the most prominent factors identified by several studies as influencing workforce requirements on projects. While actual total costs are usually not available at the start of a project, cost estimates can be adopted to gauge the project's size. Bou Hatoum et al. (2021) conducted a study estimating the impact of selected factors on construction projects. The workforce consisted primarily of inspectors classified by experience into junior, intermediate, and senior levels. For junior inspectors, an average of 0.45 FTE was recorded when project costs remained within the contract amount, increasing to 0.8 when costs exceeded the contract amount. Similar increases were recorded for both intermediate and senior-level engineers. A statistical test, the Wilcoxon test, was used on the data, showing a significant increase in the number of junior and intermediate inspectors needed for projects when costs exceeded the contract amount.

Most studies estimating inspectors and workforce on construction projects rely heavily on the cost of each project, as this is the best indicator of the project's size. Studies employing regression analysis typically use cost as the main variable for single-variable analysis and include it as one of the independent variables for multivariate analysis. For instance, Wong et al. (2008) used the contract amount along with project type, construction method, degree of mechanization, etc., in a multivariate regression analysis of construction labor demand. TxDOT and SCDOT also incorporated some form of cost or contract estimate in their regression models (Bell and Brandenburg 2003; Kim et al. 2016).

Project Type

Project type refers to the classifications assigned to projects handled by the STA. Across different agencies; there are various ways by which project types are defined. Some STAs go further by classifying the actual tasks carried out on the project, often referred to as the "work type", which can sometimes be used as a proxy for the project type. The FHWA defines project types across nine categories (Li et al., 2019), including Road (New construction/expansion), Road (Rehabilitation/resurfacing), Bridge (New), Bridge (Replacement), Bridge (Rehabilitation), Other (ramps, curbs, shoulders, sidewalks, drainage, retaining walls, etc.), Other (guardrails, lights, signals, strips, signs, landscaping, etc.), Other Structures (rest areas, weigh stations, toll stations, etc.), and Research.

Several studies (Bell and Brandenburg 2003; Kim et al. 2016; Persad et al. 1995; Wong et al. 2008) have identified project type classifications as influencing the number of inspectors and workforce required for projects. Bou Hatoum et al. (2021) showed that, in addition to the level of complexity and project size, project type was a factor affecting inspection staffing for construction projects. Their study observed variations in inspector requirements across project types for each inspector level. For instance, junior-level inspectors were more frequently required for roads, followed by bridges, roadside enhancements, and other types. The variation was found to be statistically significant using the Kruskal-Wallis test. Additionally, DOT studies that implemented regression models for workforce forecasting also highlighted the importance of project type in their models. TxDOT found that demand for its workforce increased by a factor of 0.66 due to cost and project type (Kim et al. 2016). SCDOT used data from 130 highway construction projects and over 11,000 employee payroll entries for their manpower prediction, utilizing project type as one of its predictors (Bell and Brandenburg 2003). Wong et al. (2008) also applied multivariate regression analysis on its project dataset, using project type among other predictors.

Complexity Level

Projects of a similar type can vary significantly in execution complexity. Based on this complexity, projects can be classified as minor, moderate, or major (Li et al. 2019). Minor projects include non-complex, straightforward tasks such as overlays, maintenance projects, and simple widening with minimal right-of-way. Moderate projects typically involve minor roadway relocations, simple bridge replacements, and minor roadway work. Major projects include new highway constructions, major relocations and reconstructions, significant widening, and new interchanges and bridges (Bou Hatoum et al. 2021; Li et al. 2019).

Bou Hatoum et al. (2021) demonstrated that different levels of inspectors are required depending on a project's complexity. For example, the study found that an average of 0.52, 0.49, and 1.44 FTE junior inspectors were needed for minor, moderate, and major projects, respectively. Similarly, an average of 0.72, 0.99, and 2.97 FTE intermediate inspectors were required for minor, moderate, and major projects. For senior inspectors, the average FTE needed was 0.79, 0.98, and 1.9 across the complexity levels from minor to major projects. The differences in these requirements were found to be statistically significant using the Kendall Tau-b test, particularly for intermediate and senior inspectors.

Additionally, other studies have identified project complexity as a strong predictor of manpower requirements. Wong et al. (2008) found project complexity to be a critical factor in their multivariate analysis, which included variables such as project type, contract amount, and degree of mechanization, among others.

Cost/Schedule Performance

This factor refers to how closely the final cost and schedule of a project align with the initial budget or timeline. Projects can either be under budget, on budget, or over budget, and depending on each project's status, this influences the final number of inspectors required for its completion. Bou Hatoum et al. (2021) showed that projects within budget and schedule, and those that run over, have varying inspector requirements across levels. For instance, junior-level engineers require an average FTE of 0.45 when the project stays within the contract amount, compared to 0.8 when it exceeds the contract sum. A similar trend is observed at the intermediate inspector level, with an average FTE of 0.78 for projects within budget and 1.35 for those over budget. Similar variations occur when considering the schedule, where different inspector levels have varying average FTE requirements. The study used the Wilcoxon test, and these variations were found to be statistically significant.

External Factors

Some selected external factors are also known to affect staffing requirements for projects. As reported in NCHRP Synthesis 450 (Taylor et al. 2013), responses from experts were gathered regarding their judgment on whether certain external factors would increase, decrease, or have no effect on the workforce requirements of a given project. The responses were collected from 13 STAs, and the factors were grouped into administration, engineering, and inspection staff categories.

Poor schedules, plans, and estimates were ranked highest for increasing workforce requirements in the administration and inspection units. These findings are consistent with past literature, which linked increases in personnel requirements to some form of design error. Additionally, the survey revealed that an increase in the construction experience of staff tends to reduce the construction inspection requirements for a project.

The method of project delivery and funding systems were also observed to impact staffing requirements. While several respondents acknowledged using a design-build contract, about half agreed that this method reduces workforce requirements, more than half suggested no change, and only a few noted a potential increase in staffing needs. Most respondents who acknowledged using warranties for their construction also reported no changes in workforce requirements, with only a few mentioning an increase or decrease.

As expected, regarding expedited staffing requirements, more than half of the respondents indicated that an increase in workforce is typically observed when a project is expedited. The remaining respondents noted no change, which could be attributed to constraints in recruiting additional personnel, leading to a significant increase in the workload of the assigned inspectors. Other factors considered but not extensively discussed in the survey include weather, traffic, limited materials, location in rural or metropolitan areas, contractor experience, and increased funding, among others.

Other Factors

In addition to the common factors influencing workforce requirements, other factors include construction methods, degree of mechanization, management attributes, site locations, construction technology, project deadlines, and cooperation among designers and contractors. Past studies have established that these factors affect the total workforce needed to complete construction projects. For example, Wong et al. (2008) applied multivariate regression analysis on 54 projects, incorporating factors like construction method, degree of mechanization, management attributes, expenditure on electrical and mechanical services, and site location, alongside major factors such as cost, complexity, and project type.

The construction method plays a key role in determining labor input and its composition. For instance, methods that emphasize the use of prefabricated components can reduce labor requirements, and certain methods are more efficient than others regarding inspector needs. The degree of mechanization also significantly impacts labor requirements. While this can sometimes be inferred from project costs, it directly affects the required workforce. Specifically, increased automation generally leads to reduced workforce needs.

Plebankiewicz and Karcińska (2014) examined selected factors impacting the workforce in construction, including those less commonly considered. The study identified factors such as contractual deadlines for project completion, construction technology, cooperation between designers and contractors, and workforce availability. The analysis highlighted the relative importance of these factors, showing that deadlines, the amount of work, and construction technology are more critical compared to other considerations.

Chapter 4. Forecasting Model Development

Model Development

Past studies indicate a log-log linear relationship between project costs and the level of person-hours required for completion. Furthermore, it has been established that cost and project types are the best predictors of the level of person-hours required for any given project. Linear regression models were developed for each work type present in the historical ARDOT data. The breakdown of the number of projects based on work type indicates that specific work types have a smaller number of projects than required for fitting a linear regression model, as depicted in Figure 11. It was therefore important to group some of the work types together to build a linear regression model for their forecast.

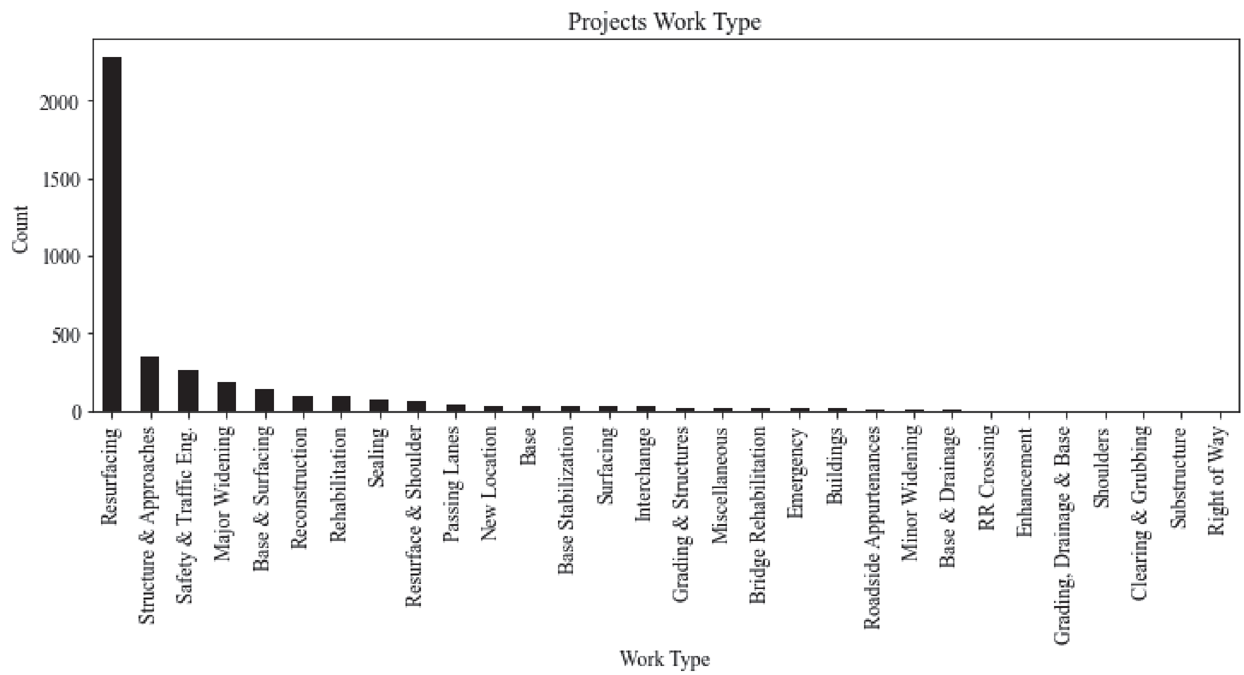


Figure 11. Project Count Based on Work Type

To achieve the grouping of the work types, two methods were explored. The first involved segregating work types based on the descriptions of the projects to which they are assigned. Common themes regarding the type of work being done among the projects categorized for each work type were assessed, and groupings were made to ensure that the number of projects within each group was sufficient (30 or more projects). The second approach involved using the k-means machine learning algorithm for clustering work types based on the distribution of their level of person-hours required for project completion. Additionally, each group fulfills the requirement of having 30 projects or more for linear regression analysis. The classifications based on descriptive themes were preferred based on ARDOT's correspondence and expert engineering judgments. Classifications of the work types based on the descriptions used are presented in Table 7 below. To accommodate additional future project types that might not currently exist, a project group called "all projects" was also included for modeling, which takes into consideration data from all possible groups.

Table 7. Work Type Groupings for Similar Work Types with Fewer than 30 Projects.

Group 1 (39)	Group 2 (36)	Group 3 (53)
Base Stabilization (12)	Buildings (6)	Emergency (3)
Base & Drainage (2)	Minor Widening (3)	Interchange (9)
Grading, Drainage & Base (1)	Surfacing (7)	Passing Lanes (12)
Grading & Structures (2)	Roadside Appurtenances (6)	RR Crossing (2)
Base (7)	Sealing (5)	Rehabilitation (11)
Base & Surfacing (15)	Miscellaneous (9)	New Location (11)
'No Value'	'No Value'	Bridge Rehabilitation (5)

The regression models were built using project cost and the year difference as independent variables. The year difference is the difference between the current year and a predefined base year, capturing changes in the level of person-hours required due to technological advancements and other related changes that might affect employee productivity over the years. The general model is defined as expressed in Equation 2.

$$Log\ (person\_hour) = \beta_0 + \beta_1 \times \log(adjusted\ cost) + \beta_2 \times (year\_difference)$$

Equation 2: General Regression Model

The resulting coefficients of the linear regression analysis, as well as the R-squared values, are reported in Table 8 below.

Table 8. Regression Coefficient and Fitness Statistics of Forecasting Models for Project Type/Groupings

Project Type/Grouping	β_0	β_1	β_2	R^2
All Dataset	-6.956	0.974	0.029	0.808
Resurfacing	-5.933	0.875	0.052	0.735
Structure & Approaches	-3.397	0.767	0.054	0.788
Safety & Traffic Eng.	-2.647	0.668	0.081	0.722
Major Widening	-0.398	0.590	0.024	0.526
Reconstruction	-1.811	0.675	-0.070	0.828
Group 1	-6.213	0.941	0.030	0.918

Group 2	-5.560	0.867	0.104	0.740
Group 3	-5.955	0.935	0.020	0.820

This model forecasts the level of person-hours required for the entirety of the given project, regardless of employee positions. The next stage involves the distribution of the forecasted person-hours across different employee classifications.

Person-Hour Distribution

The distribution of forecasted person-hours by project is carried out based on historical distribution. The distributions vary across different project cost ranges; hence, it became important to classify the distribution based on project costs. Using a similar approach to the person-hour distribution employed in NCHRP 923, the distribution of each project type was based on the historical distribution of each quartile of project costs within the work type or group. The historical distribution of total person-hours for projects within the cost range of the first quartile, second quartile, third quartile, and fourth quartile of each work type or group was estimated. The ratio of the hours used by each job classification to the total person-hours for the entire project was calculated for each individual project. The mean and the fifth and 95th percent confidence intervals for the actual ratio for each work type and cost quartile were estimated. This provides the option to use the average ratio or a more/less conservative ratio for estimating hours for any given project. Tables 9 and 10 show the ratios for selected job classifications across different work types and groups.

Table 9. Distribution for Project Types Across Cost Quartiles and Selected Job Titles (Mean)

Project Type	Cost Quartile	Constr. Inspector	Engineer	Constr. Aide
Safety & Traffic Eng.	1	0.4067	0.0181	0.3446
Safety & Traffic Eng.	2	0.3567	0.0347	0.5069
Safety & Traffic Eng.	3	0.3607	0.0175	0.3716
Safety & Traffic Eng.	4	0.2733	0.0454	0.4776
Group 1	1	0.3244	0.0588	0.3582
Group 1	2	0.4633	0.0262	0.3935
Group 1	3	0.3876	0.0434	0.4588
Group 1	4	0.3634	0.0405	0.3400
Resurfacing	1	0.2306	0.0326	0.4511
Resurfacing	2	0.2520	0.0435	0.4204
Resurfacing	3	0.2697	0.0389	0.3952
Resurfacing	4	0.2144	0.0416	0.4211
Major Widening	1	0.2175	0.0190	0.3846

Major Widening	2	0.2774	0.0397	0.3976
Major Widening	3	0.2885	0.0839	0.3469
Major Widening	4	0.2573	0.1019	0.2991
Structure & Appr.	1	0.2565	0.0463	0.4651
Structure & Appr.	2	0.3316	0.0178	0.4519
Structure & Appr.	3	0.3093	0.1394	0.3248
Structure & Appr.	4	0.3222	0.0651	0.3076
Reconstruction	1	0.2873	0.0162	0.4626
Reconstruction	2	0.1198	0.0948	0.6494
Reconstruction	3	0.2970	0.0856	0.3214
Reconstruction	4	0.2090	0.0970	0.3376
Group 2	1	0.1962	0.0575	0.5904
Group 2	2	0.5387	0.0925	0.2423
Group 2	3	0.5572	0.0070	0.2742
Group 2	4	0.3098	0.1414	0.2234
Group 3	1	0.3914	0.0303	0.4489
Group 3	2	0.3478	0.0507	0.3461
Group 3	3	0.3491	0.0459	0.3429
Group 3	4	0.1846	0.0720	0.4181

Table 10. Distribution for Project Types Across Cost Quartiles and Selected Job Titles (Mean) (Continued)

Project Type	Cost Quartile	Adv. Engineer	Constr. Proj. Coord.	Constr. Mat. Insp.
Safety & Traffic Eng.	1	0.0156	0.0786	0.0127
Safety & Traffic Eng.	2	0.0264	0.0030	0.0520
Safety & Traffic Eng.	3	0.0345	0.0702	0.0460
Safety & Traffic Eng.	4	0.0312	0.0560	0.0899
Group 1	1	0.0134	0.0000	0.1455
Group 1	2	0.0031	0.0001	0.1088
Group 1	3	0.0022	0.0755	0.0289
Group 1	4	0.0044	0.1252	0.1014
Resurfacing	1	0.0141	0.0251	0.2013
Resurfacing	2	0.0230	0.0190	0.2101
Resurfacing	3	0.0199	0.0208	0.2141
Resurfacing	4	0.0249	0.0222	0.2061
Major Widening	1	0.1774	0.0558	0.0963
Major Widening	2	0.0805	0.0413	0.0861
Major Widening	3	0.0850	0.0561	0.0958
Major Widening	4	0.0640	0.0900	0.1304

Structure & Appr.	1	0.0445	0.0463	0.0964
Structure & Appr.	2	0.0403	0.0549	0.0457
Structure & Appr.	3	0.0852	0.0249	0.0620
Structure & Appr.	4	0.0669	0.0996	0.0780
Reconstruction	1	0.0000	0.0150	0.2180
Reconstruction	2	0.0273	0.0434	0.0430
Reconstruction	3	0.0251	0.1155	0.1087
Reconstruction	4	0.1594	0.0328	0.1285
Group 2	1	0.0263	0.0000	0.0516
Group 2	2	0.0101	0.0019	0.1103
Group 2	3	0.0007	0.0487	0.1085
Group 2	4	0.0956	0.1522	0.0223
Group 3	1	0.0389	0.0343	0.0485
Group 3	2	0.0330	0.1077	0.0805
Group 3	3	0.0082	0.1326	0.0719
Group 3	4	0.0785	0.1092	0.0772

Project Timeline Distribution

Following the distribution of the forecasted hours into various job titles, the next step involves the hour distribution over time. The time unit of interest for the forecast is the monthly hours spent on each project from its inception to completion. To understand the hourly distribution of projects over time, it is important to examine the historical trends of completed projects' logged hours. The average monthly person-hours per inspector over the months of the year are presented in Figure 12. An obvious trend can be observed across the projects' hours from the first month of the year to the last.

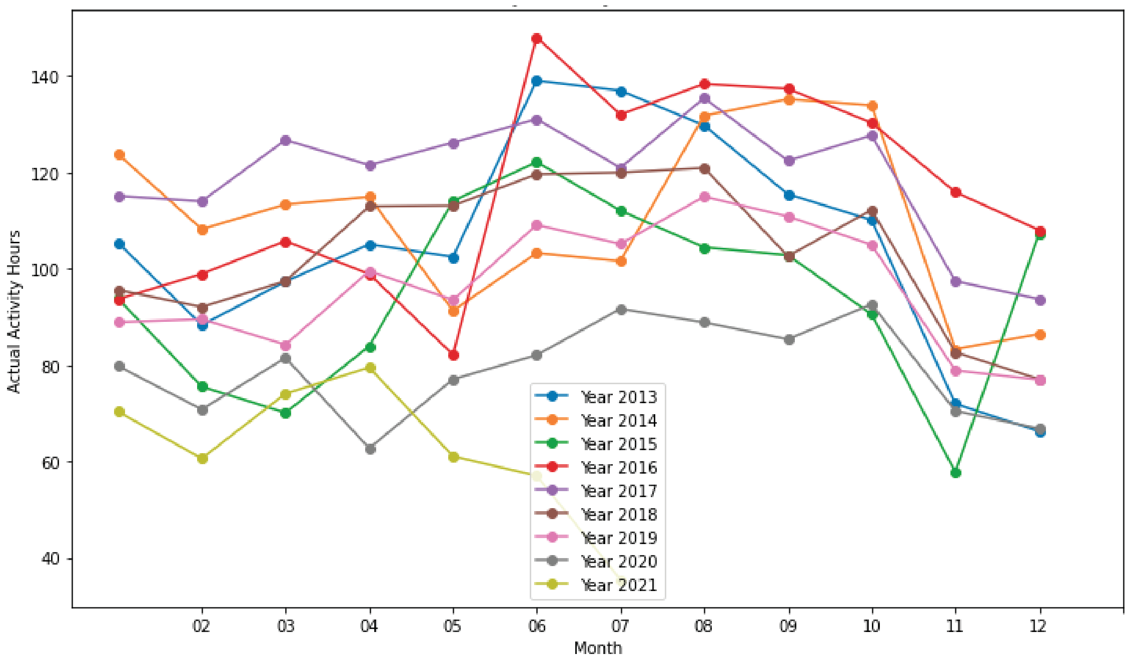


Figure 12. Average Activity Hours Over the Month for Each Year

An in-depth look into various historical projects for project types indicates a wide variation in the number of months spent on projects. This prevents the possibility of aggregating the timelines of similar projects. To overcome this, formulations for normalizing projects' hourly distribution over time were explored. The following Equation 3 allows for the possibility of expanding and squeezing the hourly distribution depending on the needs of each project type.

$$W_{SX} = \sum_{Y=1}^{t} W_Y + \left[\left(\frac{n}{\mu} * X\right) - t\right] \times W_{t+1} - \sum_{z=0}^{X-1} W_{sz}$$

$$\left(\frac{n}{\mu} \times X\right) - 1 < t \leq \frac{n}{\mu} \times X \qquad\qquad t \in \{Z^+ \cup 0\}$$

Equation 3: Formulations for Normalizing Projects' Hourly Distribution Over Time

Initialize $W_{S0} = 0.$

Where μ represents the number of stages

X refers to the Xth stage of μ

W_t is the number of hours in the tth month

n is the number of months (for the current project estimate)

To establish a representative distribution ratio for each project type, the most frequently occurring duration is employed for the project types. This is expected to be the typical duration for such types; hence, future similar projects are expected to have similar lengths. Other historical project types are normalized to a similar length using the aforementioned mathematical method, and this is stored as the timeline distribution for such project types.

New projects use the stored historical distribution, establishing the distribution timeline for the standard duration of such types. Furthermore, the normalization method is used to adapt the distribution generated to accommodate the proposed number of months for project completion. A flowchart for the timeline distribution is shown in Figure 13.

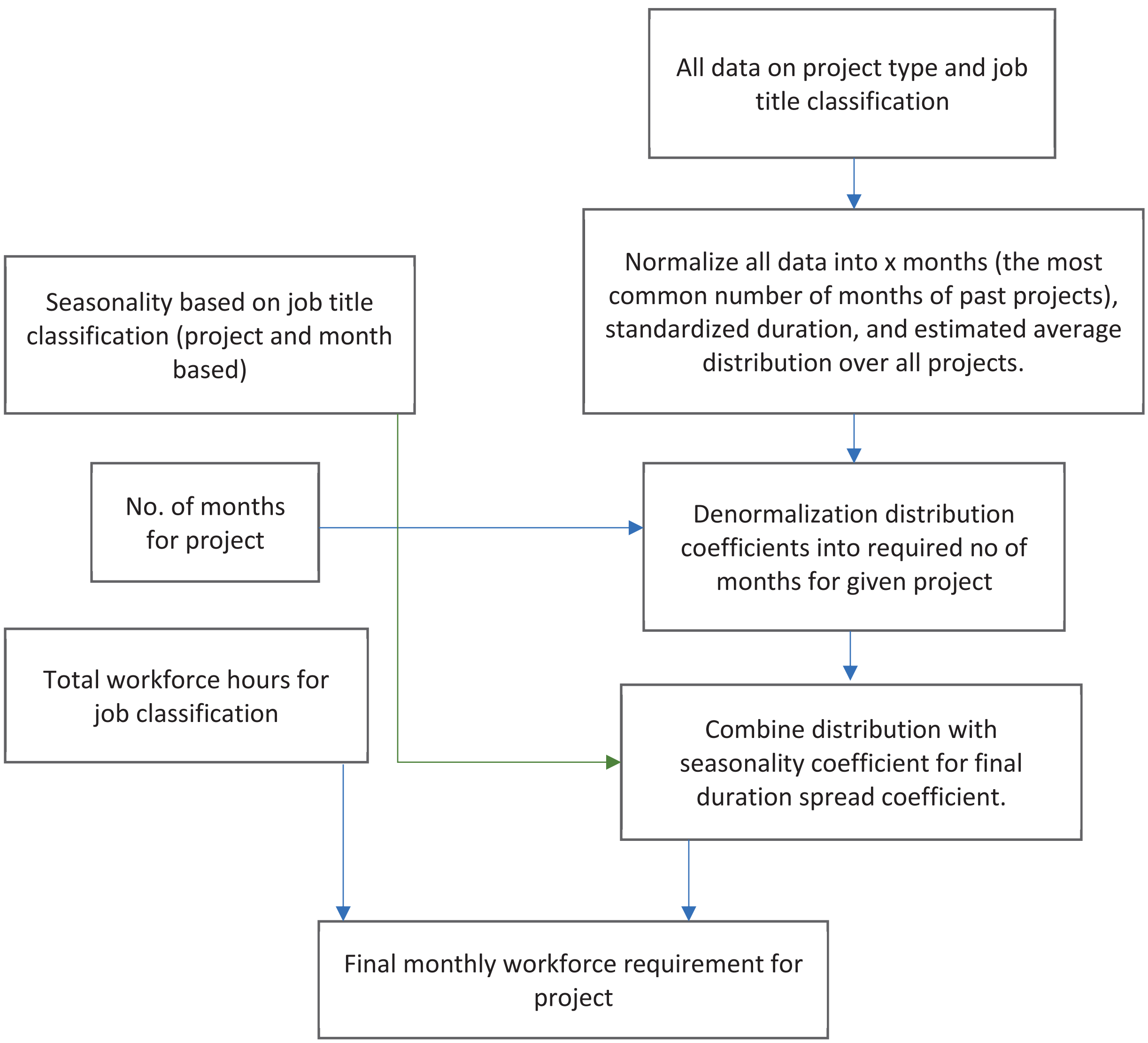


Figure 13. Flowchart for Timeline Distribution

Person-Hours to Number of Inspectors

Another request for the project involves converting the estimated man-hours to the number of inspectors required to complete each project. Based on correspondence with ARDOT, inspectors are defined by selected job titles, which are listed in Table 11, with an additional column indicating the inspectors of interest. The total number of inspectors required for projects depends on the summation of the forecasted hours of these selected job titles.

Table 11. Job Title List and Work Hour Inclusion

Job Titles	Record Hours
Staff Engineer	No
Senior Engineer	No
Advanced Engineer	Yes
Construction Project Coordinator	Yes
Engineer	Yes
Construction Inspector	Yes
Construction Materials Inspector	Yes
Resident Office Tech	No
Construction Aide	Yes
Field Clerk	No
Intern	No
Seasonal Employee	No

A basic analysis of the project hours shows a wide variation in the number of hours logged each month for each employee. This variation limits the credibility of the mean as an average for the hours expected by each inspector for the month. The median is a more reliable estimate and has been adopted and approved for conversion estimation purposes. The specific hours for the inspectors are synthesized in Table 12.

Table 12. Summary Statistics of Work Hours Across Individual Inspectors

Month	Mean	Std	25%	Median	75%
1	104.09	48.51	72.38	115.00	140.63
2	95.44	44.29	66.19	102.50	128.00
3	102.85	51.92	67.25	106.50	141.00
4	108.28	49.82	78.25	113.00	142.69

5	107.73	51.13	75.00	111.00	142.00
6	130.49	56.89	97.25	140.50	171.00
7	124.98	53.78	96.00	134.25	161.50
8	123.76	67.26	67.75	139.50	175.00
9	125.47	51.03	96.00	131.00	160.13
10	126.94	54.00	95.00	131.25	164.75
11	95.07	45.70	62.50	96.88	130.50
12	93.32	43.55	64.00	100.25	124.75

Chapter 5. Software Design and Implementation of Cursor

This chapter presents the design of the software architecture and implementation of the forecasting tool. The tool was developed as a web application accessible through a web browser. Details provided in this chapter include an extensive overview of the back-end and front-end design of the web application, database design, and the update and maintenance of the tool.

Overview

Construction workforce forecasting software (CURSOR) is a forecasting tool that allows users to input construction project portfolios with project characteristics, run forecasting models, and output construction workforce estimates by role and RE offices. This is an update from the existing forecaster application, which has outdated system requirements and limited functionalities. The new tool is a web-based application hosted locally on ARDOT's servers. This makes it accessible via any web browser and allows multiple engineers to utilize the tool.

Software Architecture

CURSOR is designed to efficiently manage complex data processing for forecasting purposes. The back-end architecture is pivotal in ensuring the application's robustness, scalability, and security. Additionally, it is integrated with external databases to automate input for its forecasting capabilities. The system's structure is illustrated in the context diagram presented in Figure 14.

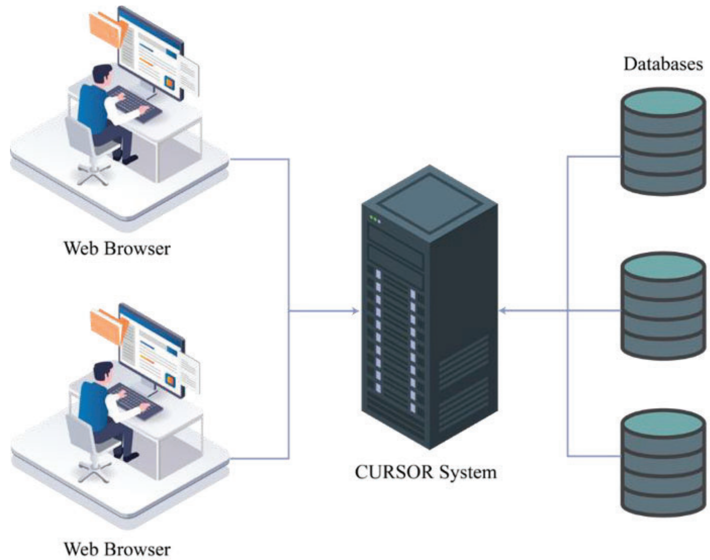


Figure 14. Context Diagram for CURSOR

To illustrate the flow of data into and out of the system at a high level, a data flow illustration is provided in Figure 15. The two major data sources are user input and historical data stored in the databases. The system generates its output prediction data, which is also considered in the flow, including its generation and storage.

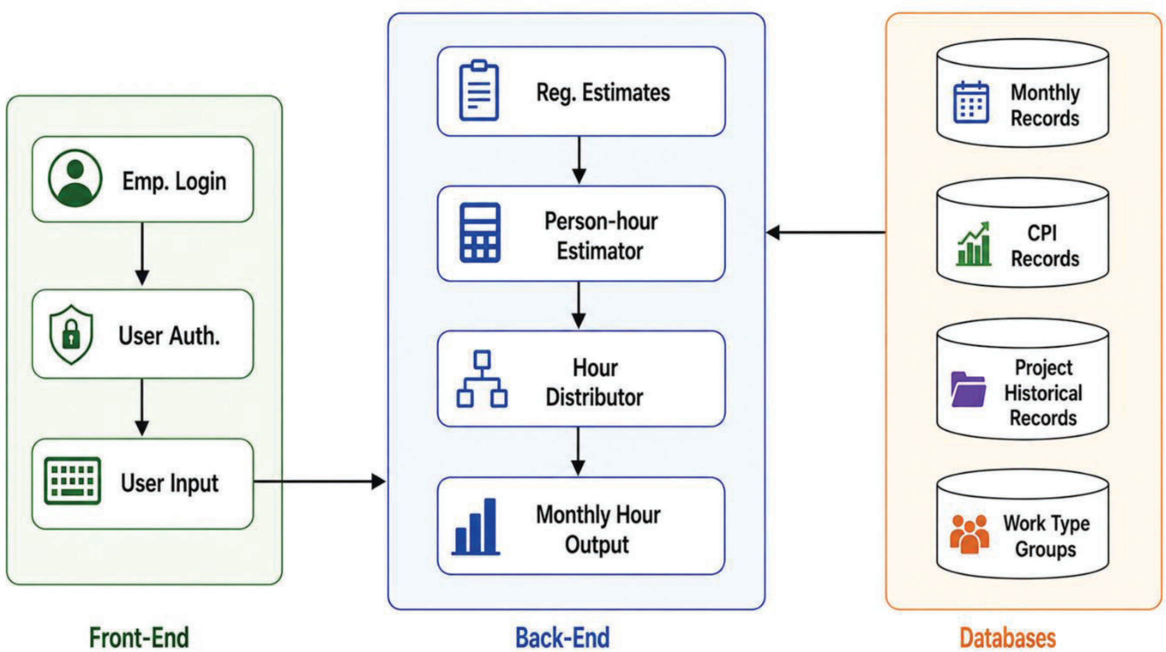


Figure 15. Data Flow Into and Out of the CURSOR System

Back-End

View Introduction

This report details two views from the “4+1” view model: the Logical (Module) View and the Process (Component-and-Connector) View. The Logical View outlines the system’s layered structure and focuses on the functionality available to end users. In contrast, the Process View describes the client-server architecture, highlighting aspects such as concurrency, synchronization, and system integrity. While the Logical View illustrates how the system is organized through functional code units or modules, the Process View emphasizes the system’s operational structure. A use case scenario is also presented to demonstrate user interaction with the system.

Logical View

This view presents the system architecture from a functional perspective, detailing how the various components of the tool interact and work together to achieve its objectives. The architecture is typically represented graphically as shown in Figure 16, accompanied by descriptions that explain the roles and interactions of each component.

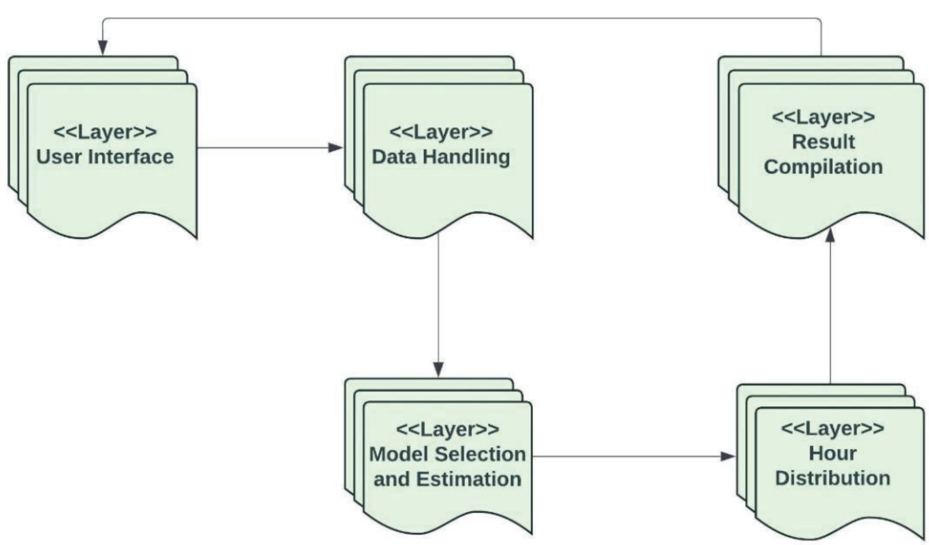


Figure 16. Logical View Illustration

For illustration purposes, the tool's major components are divided into five key layers. The *User Interaction Layer* focuses on the interface where users engage with the system. The *Data Handling Layer* manages the necessary data to ensure smooth system processing. The *Model Selection and Estimation Layer* is responsible for selecting the appropriate forecasting model and estimating the total person-hours required. The *Hour Distribution Model* redistributes the estimated hours across the relevant timeline for each project being forecasted. Finally, the *Result Compilation Layer* organizes the forecasted project details for reporting through the front-end application.

The *User Interaction Layer* serves as the system's access point, enabling users to engage with its core functionalities. It includes the *Authentication Module*, which ensures that only authorized users can access the system, manage data, and perform maintenance activities. The *Application Interface Module* facilitates the flow of data between the user interface and the backend, allowing users to input data and retrieve result estimates.

The *Data Handling Layer* manages the flow of data between the user and the system, overseeing all interactions with data, including user inputs, forecast data, historical data, and preloaded data. It facilitates access to databases, enabling the system to retrieve historical data for regression estimates and forecasting purposes. This layer plays a critical role in ensuring that all necessary data is available to the system for accurate estimates.

The *Model Selection and Estimation Layer* consist of two key components: the *Selector Module* and the *Hour Estimator Module*. The *Selector Module* is responsible for identifying and selecting the most appropriate forecasting model based on work group and work type coefficients. It determines whether to apply a work-type-specific, work-group-specific, or general default model, depending on data availability. Once the selection is made, the *Hour Estimator Module* uses regression techniques to estimate the total person-hours required for each forecasting project based on the chosen model.

The *Hour Distribution Layer* takes the estimated total person-hours and distributes them over the project's duration. Leveraging the historical distribution of similar projects, it estimates the monthly total hours for engineers and inspectors, accounting for factors such as seasonal variations. Lastly, the *Result Compilation Layer* handles the final step of collating the forecasted data, enabling the results to be displayed to the user via the interface layer. It also provides the option to retrieve the final estimates in the user's desired format.

Process View

The *Process View* illustrates the dynamic behavior of the system, focusing on the interactions between components and the flow of data during execution. It details how the various modules collaborate in real-time to produce the desired output. Key processes in the architecture include data collection, model generation, and the distribution of results over time. A detailed process view has been presented in Figure 17.

Upon launching the application, authentication is performed via the web interface, triggering the loading of data from the database. Using the loaded historical data, prediction models are generated, and user inputs are combined with the estimated coefficients for forecasting. Throughout the workflow, decision points dynamically select the appropriate coefficients based on input data, including the selection of work groups, work types, and distribution models. The total hours for each record are estimated using the selected regression model and then further broken down by job types through the hourly distribution models across the project duration.

The estimated job hours are then processed by the hour distribution model, which allocates hours over the project timeline based on historical and seasonal patterns. Finally, the results are compiled across the RE offices, and the detailed output is exported in various formats according to user preferences. This view highlights the real-time flow of operations as tasks progress through different stages of the system, ensuring efficient data management and accurate forecasting.

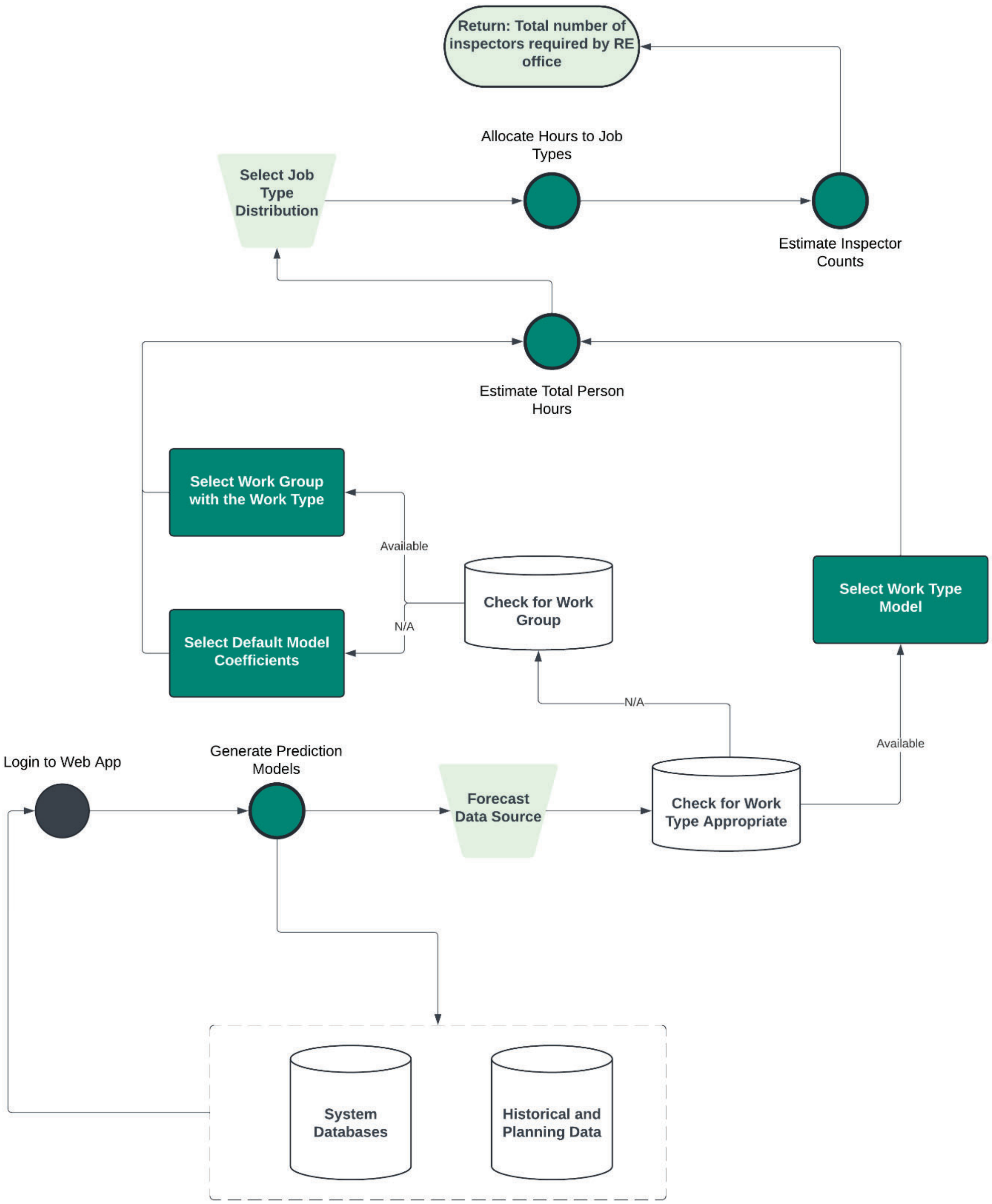


Figure 17. Software Architecture for CURSOR Web Application

Scenario

Use Case: Forecasting

- Description: Basic use of the software tool to quickly forecast engineering requirements using data from DOT's planning database
- Primary Actor: Engineer/Planner (User)
- Goals: Generate forecasts of RE office engineering requirements.

- **Preconditions**
    - The Engineer/Planner must have valid ARDOT login credentials.
    - The user must be authorized to access and use the system.
- **Basic Flow**
    - The user logs into the software interface using ARDOT login credentials.
    - The system loads the projects from the planning database into its memory for further user inputs.
    - The system highlights any required missing fields from the projects.
    - The system presents a list of projects categorized by RE offices, offering a drop-down for office selection.
    - The user navigates through the RE offices and manually inputs any missing key data.
    - The system activates the button to generate forecasts.
    - The system processes input data through regression analysis and forecasting steps to generate output results.
    - The system provides the results, offering export options in Excel and PDF formats.
    - The user adjusts dynamic inputs, such as the proposed crew complement and existing crew complements, for each RE office.
- **Alternate Path**
    - The user logs into the software interface using ARDOT login credentials
    - The user formats the input data according to the system's requirements.
    - The user uploads the properly formatted data.
    - The system highlights any missing required missing fields from the projects.
    - The system presents a list of projects categorized by RE offices, offering a drop-down for office selection.
    - The user navigates through the RE offices and manually inputs any missing key data.

- The system activates the button to generate forecasts.
- The system processes input data through regression analysis and forecasting steps to generate output results.
- The system provides the results, offering export options in Excel and PDF formats.
- The user adjusts dynamic inputs, such as the proposed crew complement and existing crew complements, for each RE office.

Application Programming Interface (API)

End Points

The system incorporates three key controllers: JobDistributionController, PredictionController, and WorkTypeController. Each controller plays a vital role in managing the data interactions between the user interface and the back-end, ensuring seamless communication and processing of user inputs and system outputs.

The JobDistributionController presents job distribution options to users through the interface. It retrieves data from the JobDistributionType Enum, a structured set of constants that defines the available job distribution types. These options are displayed in a drop-down menu on the UI, enabling users to select their preferred job distribution method.

The PredictionController handles requests for generating predictive outputs and requires user authentication to function. It leverages the PredictionFactory class to invoke the GetOutputPredictions method, which retrieves the prediction results. The final list of predictions is then returned to the user interface for further processing.

Finally, the WorkTypeController operates similarly to the JobDistributionController but focuses on providing work type options via the WorkTypes Enum. This list is used to populate the corresponding drop-down menu on the user interface, allowing users to select the appropriate work type.

Together, these controllers ensure seamless data flow between the front-end user interface and the backend, facilitating smooth interactions and efficient processing.

Program

The software tool is equipped with a well-defined set of service configurations and security settings to ensure efficient operation and secure communication. It leverages two primary service types: transient services and singleton services, each employed based on specific operational needs.

Transient services create a new instance of an object for every request, providing fresh resources for each operation. In this system design, *MySqlFactory* is configured as a transient service, ensuring that each interaction with the MySQL database is managed by a newly instantiated factory. This approach guarantees that each database operation remains independent, preventing shared state or data leakage across requests.

Singleton services, another type utilized in this development, maintain a single instance throughout the application's lifetime. This means that all objects and requests share the same instance, promoting memory efficiency and consistent behavior. Services configured as singleton services include *HistoricalDistributionRepository*, *HistoricalRecordRepository*, *CpiRepository*, *WorkGroupRepository*, *NormalizedHistoricalDistributionFactory*, *CostRatioFactory*, *RegressionCoefficientsFactory*, *JobManHourPercentageFactory*, and *PredictionFactory*. This configuration benefits components by providing shared resources and data that remain constant across requests, minimizing the need for repeated initialization and ensuring reliable access to critical repositories.

The software implements robust authentication using JwtBearerDefaults.AuthenticationScheme to ensure secure authentication. Configuration for the authentication is integrated through Azure Active Directory, as specified in the appsettings.json file. AzureAd provides a centralized way through which user authentication is managed so only authorized users have access to the system.

To handle external requests, the system employs an open CORS policy that allows any origin, method, or header. While this configuration is useful for serving a wide range of clients, the open policy could be overridden by server-side configurations, giving access to administrators to restrict access based on security requirements.

Additionally, forwarded headers; XForwardedFor, XForwardedProto, and XForwardedHost were integrated to preserve the details of the original client's request when passing through proxies. To ensure data integrity, the system clears known networks and proxies, reducing the risk of malicious actors injecting false header information.

Class Libraries

Records

The software features several record objects designed to store and manage specific types of data. The records are the basic building blocks for processing and estimating the system's outputs, ensuring the accurate mapping of user inputs and historical data to generate predictions.

The *AdjustedInputRecord* holds the user inputs, specifically creating a record of the *PredictionInputRecord* with the corresponding adjusted award amounts. The records are a modified version of the original input reflecting the award amount adjusted for inflation. The *PredictionInputRecord* stores the original user inputs. It contains vital details such as the project number, start date, job distribution type, and other relevant data. It also stores the estimated hour and monthly distribution types resulting from the job distribution type.

The *PredictionOutputRecord* contains records from the *PredictionInputRecord*, along with the estimated values, including the predicted *TotalManHours*, predicted *JobManHours*, and predicted *JobHourDistributions*. This record serves as a container to provide easy access to the input data and predictions generated by the system.

Tracking of cost and job hours is managed through various objects. The *CostRatioRecord* handles the storage of the cost ratio, adjusted award amount, year difference, and the percentage of total hours worked by each job type mapped with the corresponding *HistoricalRecord* data. The *JobManHourPercentageRecord* estimates the percentage of man-hours for each job type based on the statistical distribution of the corresponding adjusted award amount. Records for the fifth percentile, mean, and 95th percentile are estimated and stored in the record. The *JobManHourRecord* simply records the number of hours worked by each job type for each project in the historical records.

The *HistoricalRecord* and *HistoricalDistributionRecord* objects handle the historical data utilized in the system. Specifically, the *HistoricalRecord* captures the data from the historical_record table, while the *HistoricalDistributionRecord* includes additional data such as job types and work types from the monthly_historical_records table. In addition, they also provide the work type and job type Enum value, granting access to the available types. These records are vital for estimating the regression model for prediction.

Furthermore, the records contain objects such as the *CPI*, *WorkGroup*, and *WorkTypeGroupMatch*. These records help further organize the work types for regression purposes and track the cost performance index over time. The CPI object stores data about the cost performance index for each year, allowing the system to automatically adjust for inflation over time for its regression estimates. The *WorkGroup* and *WorkTypeGroupMatch* objects define the work groups and match the work types to these groups, creating an organizational structure that automatically group projects based on their count and related work types. This ensures the adequacy of each regression estimate carried out.

These records are a major backbone of the system's data management and prediction capabilities, ensuring the smooth processing of user inputs.

Repositories

The software system features different repositories that facilitate data retrieval from the MySQL database, with each serving a specific role in obtaining and processing records relevant to job distribution, historical data, cost performance, and work groups.

The *HistoricalDistributionRepository* plays a significant role in the system as it creates the connection to the MySQL database to retrieve the historical distribution records. These records contain the historical job distribution, which are core to the system's estimation and analysis functions. It relies on the *MySqlFactory* to route the connection to the database to ensure efficient data retrieval. Similarly, the *HistoricalRecordRepository* is primarily concerned with retrieving the historical records for project details and total project hours. This is particularly important for regression estimation in the system, and just like the *HistoricalDistributionRepository*, it utilizes the *MySqlFactory* to establish and manage the database connection.

The *CpiRepository* is responsible for retrieving the CPI records, which are required to accommodate the inflationary effects of costs over time. These records are retrieved for each past historical record year and estimated for future years present in the system. As with other repositories, this also relies on the *MySqlFactory* for its database connection. The *WorkGroupRepository* is concerned with the *work_type_group_matches* table. The repository facilitates the grouping of similar work types for regression purposes in cases where work types have an insufficient number of projects.

The above-described repositories are essential to ensure the system works efficiently and has structured access to the key datasets stored in the MySQL databases.

Factories

The system's architecture incorporates several factories designed to facilitate complex calculations and object creation by leveraging data from various repositories. These factories are instrumental in automating the processes that drive the estimations and distribution calculations.

The *MySqlFactory* is designed to facilitate the MySQL database connection. Utilizing variables from the environment file, it enables all other factories and repositories to interact with the database efficiently. *The NormalizedHistoricalDistributionFactory* is another important factory that generates historical distributions for various work type and job type combinations. It utilizes data provided by the *HistoricalDistributionRepository* and creates the required distributions based on the predefined methodology for hour distributions.

The *CostRatioFactory* constructs the *CostRatioRecords* by estimating the adjusted award amount, the cost ratio by taking a ratio of the award amount and the total man-hours, the year difference based on the difference between the let year and the reference year, as well as determining if the work type belongs to a work group. To carry out these tasks, it utilizes data from the *CpiRepository*, *WorkGroupRepository,* and *HistoricalRecordRepository*. Additionally, it groups the cost ratio based on its percentiles and work type groupings, along with its award amounts. Using the *GetBins* method, it can sort the *CostRatioRecords* into four bins using their statistical quantiles generated from the adjusted award amounts.

The *RegressionCoefficientsFactory* relies on the outputs from the *CostRatioFactory* and data from the *WorkGroupRepository* to estimate the log regression coefficients based on historical data. These coefficients are stored and used for future forecasting based on user inputs for estimating total project hours. The *JobManHourPercentageFactory* is concerned with the distribution of the forecasted person-hours across different job types. It sorts the *CostRatioRecords* by the work group and calculates the percentage of total hours for each job type using key statistical markers such as the 95th percentile, fifth percentile, and mean values.

The most complex factory, *PredictionFactory*, employs data from several repositories and other factories such as *NormalizedHistoricalDistributionFactory*, *RegressionCoefficientsFactory*, and *JobManHourPercentageFactory* to generate predictions for total project hours and monthly distribution job hours. The factory employs normal distribution and historical distribution for the allocation of hours over time. A final output of the monthly project hours is provided as the output records for further processing by the user engineer.

These factories work together to streamline data processing and automate predictions to generate the needed data for workforce planning within the system.

Extensions

The extensions defined within the system provide additional functionality for the core records and enhance their utility, allowing for more complex calculations and statistical analysis. These extensions work directly on the data objects that they extend and ensure that the system can handle adjusted award amounts, critical values, and percentile groupings from *PredictionInputRecords* and *CostRatioRecords*.

The *DotEnv* utility plays a crucial role in managing the system configuration, dynamically loading the environment variables from a .env file. This approach ensures that configuration is separated from the application's source code, allowing for easier management of sensitive information like database credentials or API keys.

The *EnumTypes* class also serves as a central repository for Enums used throughout the system, including *JobTypes*, *WorkTypes*, *JobDistributionType*, *HourDistributionType*, and *MonthlyDistributionType*. Utilizing Enums ensures consistency and reduces the risk of errors by limiting values to a predefined set.

Maintenance

This section describes the steps required to maintain and update key components of the system. This is important to ensure that the system continuously generates accurate estimates. Components requiring such updates include CPI, historical records, work types, work groups, and job types.

Updating CPI Values

The CPI refers to the Consumer Price Index, which reflects the increase in the general price of items over the years. While the system can forecast future CPI values, it is important to update the values as they are published over the years. Steps to ensure this include the following:

- Add a row to the CPI table: Each row in the table represents a year and its corresponding CPI value. Additional rows should be created for each future year, and the appropriate average CPI value for the year should be entered into the table.
- Restart Application: Following the update of the table, the application must be restarted to ensure new data is loaded correctly and utilized for future estimations.

Adding Work Types

The work types possible within the system are finite; hence, new work types need to be added as options for the system when needed. Defining the right work type is essential for accurate estimation. The following are the steps required for adding a new work type:

- Add the new work type to the WorkTypes Enum: The new work type needs to be included in the WorkTypes Enum available in the EnumTypes class in the backend.
- Work groups: If the new work type has fewer than 30 records present in the historical records, it should be included in a work group within the work_type_group_matches table. This helps ensure that such projects are appropriately grouped for regression estimation purposes.
- Restart Application: Following the addition of the work type and grouping, the application needs to be restarted to ensure new changes take effect.

Editing a Work Group

Maintaining the work group is important to ensure similar work types are matched for coefficient estimation. This is necessary for work types having fewer than 30 projects in their historical records. Making changes to the work group can be accomplished by following these steps:

- Unique Work Types: Check that each work group consists of a unique combination of work types, ensuring there are no overlaps across the work groups.
- Minimum Records: Ensure the sum of historical records for all work types present in each of the groups is at least 30.
- Modify work_type_group_matches table: Make the desired changes to the work_type_group_matches table as appropriate.
- Restart Application: After modifying, restart the application to ensure the changes have been properly loaded into the system.

Adding Job Type

The job type is limited to the records in the historical data. Changes could be made to these types, and more job types could be added to the exhaustive list of job types. Steps required include:

- Add Job Type to JobTypes Enum: The new job type needed should be added to the JobTypes Enum in the EnumTypes class in the backend

- Restart Application: Once the job type has been added, the application should be restarted to ensure the changes have taken effect.

Databases

The system employs several database records. Some of these are internal, while others are external and serve as input mediums for the system. The system can connect to ARDOT's planning/program management database, feeding both historical and forecasting data into the system. Other internal database records designed for the system include the monthly_historical_records, cpi, historical_records, and work_type_group_matches databases. These are illustrated in the database diagrams as shown in Figure 18.

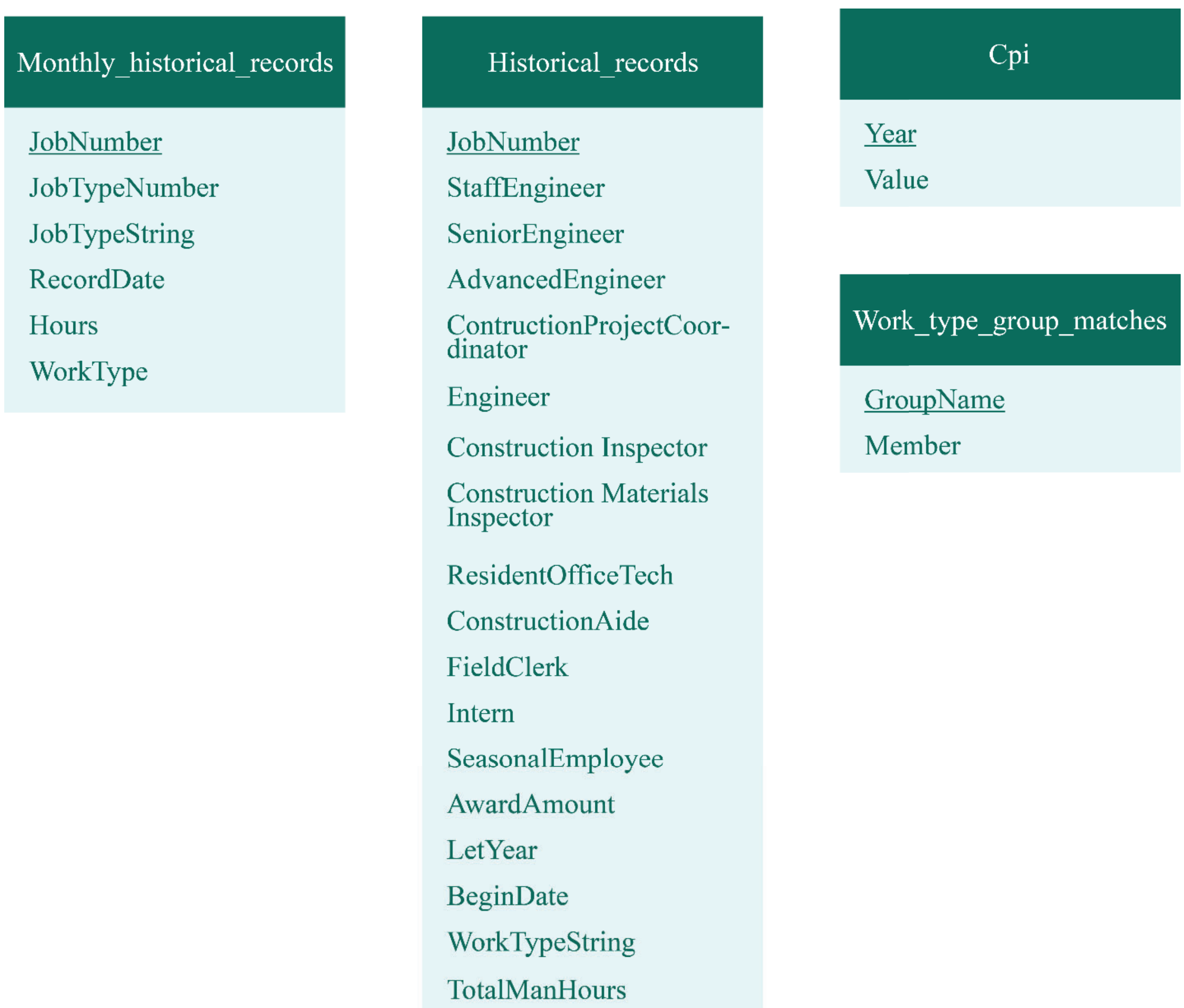


Figure 18. Database Records (System Internal)

Front-End

The system was crafted using a cutting-edge set of technologies designed to provide a seamless user experience and robust performance. At the core of the development process is Vite, a next-generation build tool that excels at comprehensive project setup and hot-module replacement. Its major advantage lies in the quick feedback on changes, allowing quicker updates and reducing iteration times.

To enhance code reliability, TypeScript is used alongside Vite. TypeScript allows static typing in the JavaScript ecosystem, enabling potential errors to be detected during the development phase rather than after being deployed in production. This was effective in developing more maintainable code, allowing better reliability in delivering features without unforeseen runtime issues.

The React.js framework forms the backbone of the user interface, with its component-based architecture allowing for dynamic and reusable UI elements. With React, the process of building the complex interface required is simplified, enabling development in smaller, manageable components. Additionally, Chart.js facilitates the visualization of the result output, allowing the system to utilize the charting functionalities of Chart.js. The chartjs-plugin-datalabels and chartjs-plugin-dragdata play crucial roles in rendering the charts, labeling them, allowing for intuitive data interaction on the system, given the complex data visualization involved.

Tailwind CSS was utilized to enhance the design and responsiveness of the user interface. With a utility-first approach, Tailwind provided the development team with tools to rapidly prototype and build consistent and responsive layouts, reducing the need for custom CSS. The integration of the @tailwindcss/forms ensures that form elements throughout the system maintain a standard and visually appealing design, helping to streamline the data input process for users.

To connect the front-end with the back-end application, the system makes use of Axios for its HTTP requests. With Axios, communication between the front-end and backend APIs is simplified, allowing the system to fetch, update, and send data as required. The application allows multiple forms of export, in the form of Excel and PDF. The React-export-excel library was used to facilitate Excel export, while HTML2Canvas and jsPDF provided the necessary tools to generate a downloadable PDF report from the system.

To control the system's security and authentication, Microsoft's MSAL library, integrated through @azure/msal-browser and @azure/msal-react, is utilized. These libraries ensure that authentication and authorization are seamless through Microsoft's secure identity platform. Additionally, user navigation through the system is streamlined through the React Router DOM, which enables smooth client-side routing and enhances the overall user experience by allowing users to move through sections without reloading the entire application.

To allow seamless deployment, the application was packaged and prepared through Docker. The Dockerfile streamlines the containerization process, ensuring the application runs smoothly and consistently across multiple environments, from development to production. The combination of the stack used helps ensure the friendly user interaction and experience required for the forecasting tasks. A screenshot of the designed front page is as presented in Figures 19, 20, 21, 22, and 23.

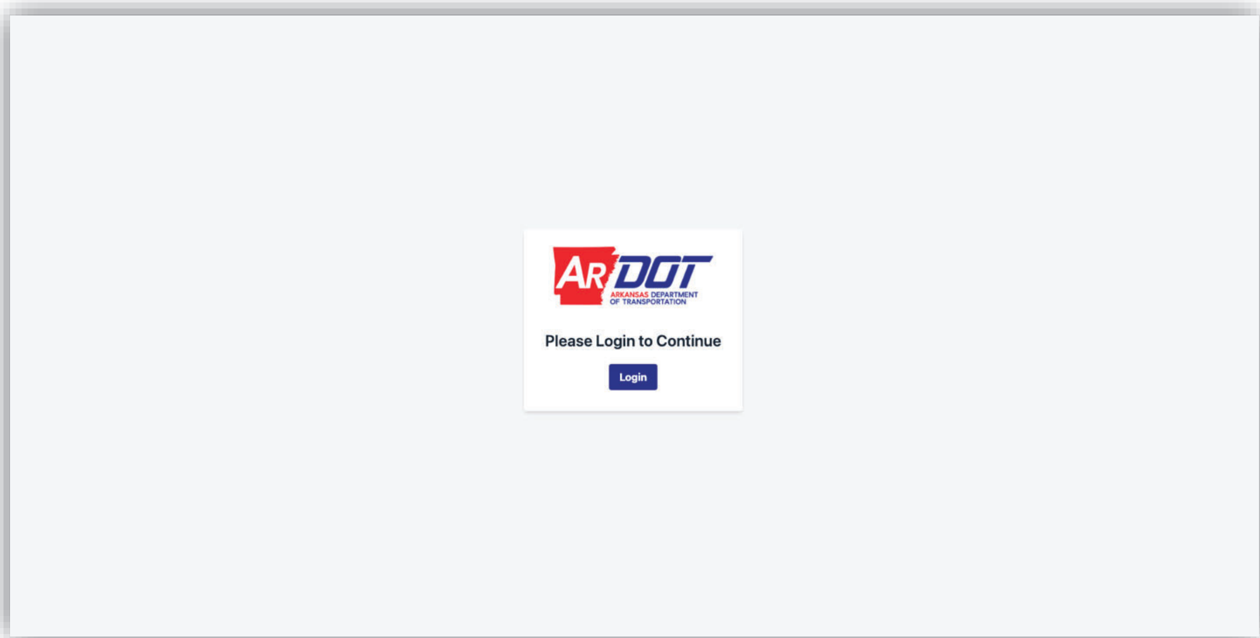


Figure 19. Login Authentication Page

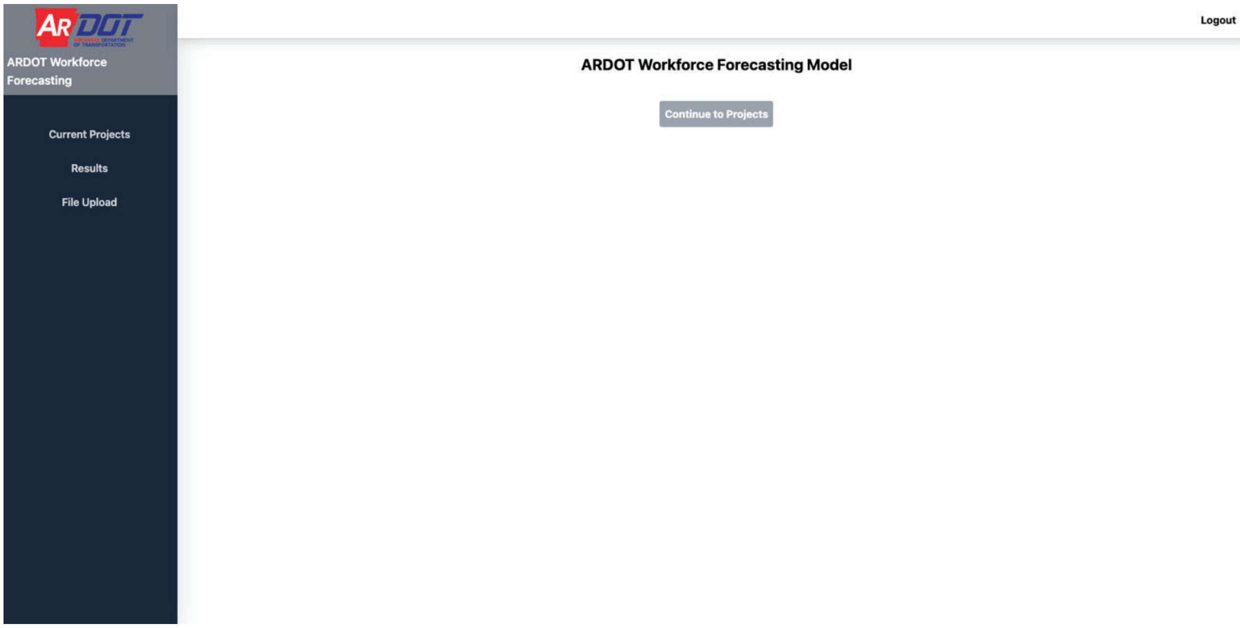


Figure 20. Welcome Page

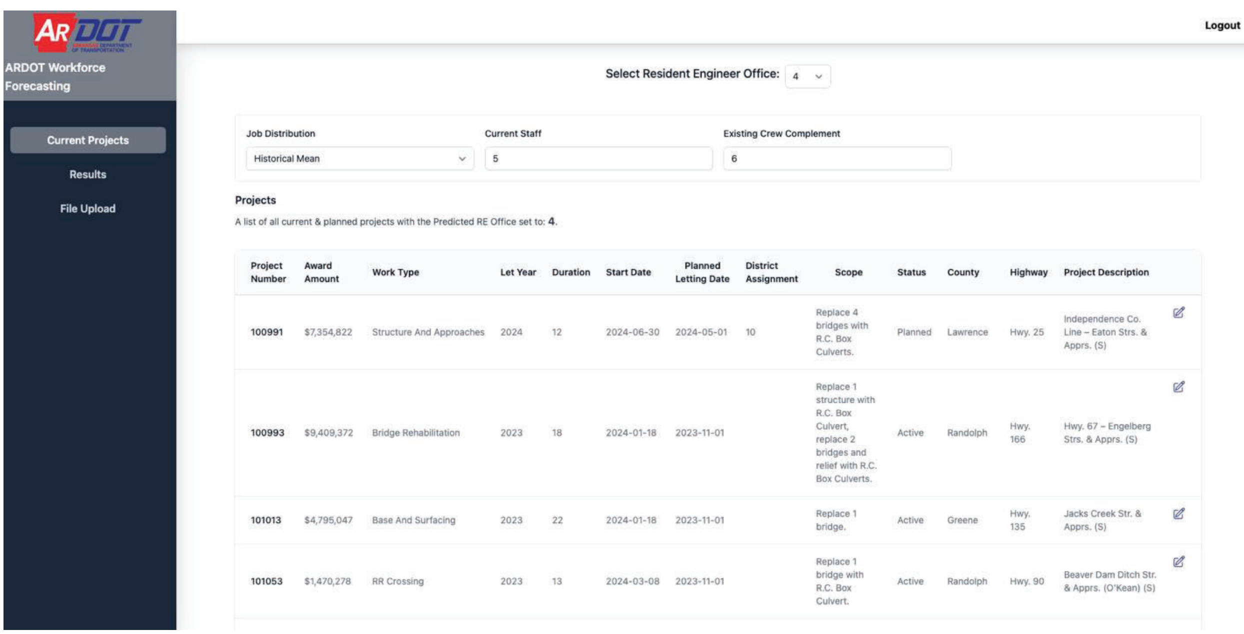


Figure 21. Forecasting Projects by the RE Office

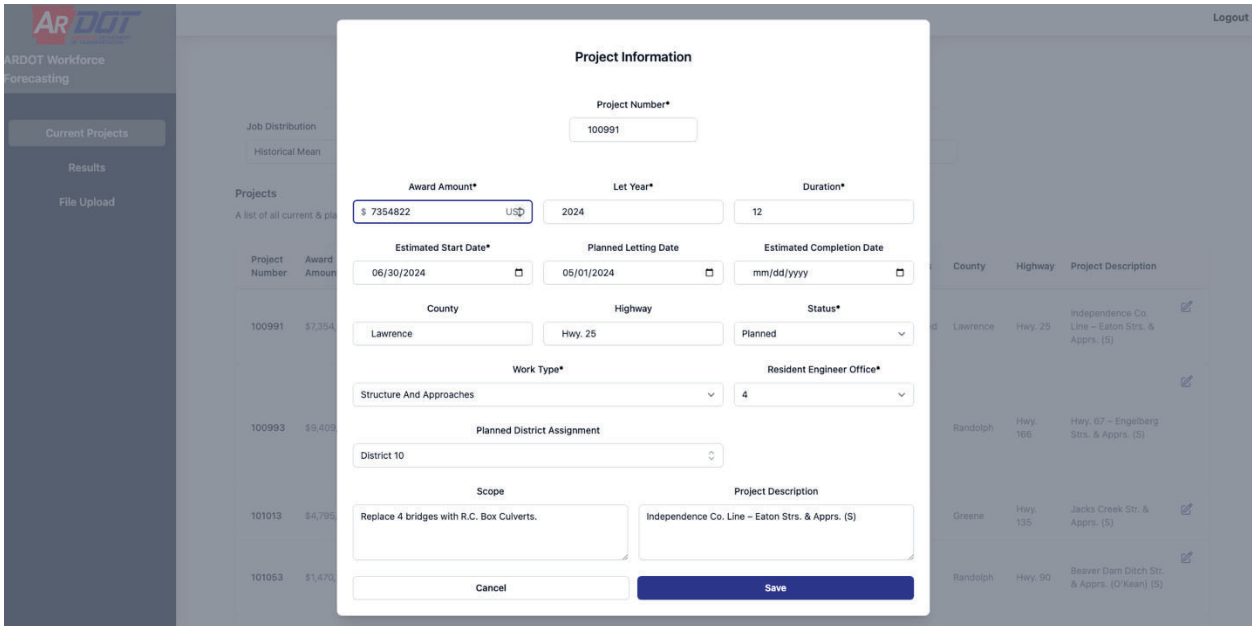


Figure 22. Project Edit Interface

Figure 23. Sample Results Interface by RE Office

Chapter 6. Conclusions, Recommendations, and Future Works

As part of the TRC2101 project, a comprehensive investigation was conducted to evaluate the existing forecasting tool and explore cutting-edge practices beyond those used by DOTs. To establish a solid foundation for model development, both human resource data and project management data were collected, offering a historical overview of workforce trends across various projects. Through a rigorous analysis of this historical data, regression models emerged as the most suitable forecasting method, particularly given the limitations of the dataset in terms of size and timeline. Through collaboration with the agency, discrepancies in the data were identified and reconciled, leading to the development of a standardized workflow for cleaning and filtering the final dataset. The forecasting models were built around similarities in work types, and each model was validated. Additionally, the distribution of job types and project timelines was seamlessly integrated into the forecasting workflow, ensuring a robust and reliable approach for predicting future project requirements.

A modern web application was developed to automate the forecasting processes and methods established during the TRC2101 project. Built using a contemporary technology stack, including C# for the backend and JavaScript frameworks for the front-end, the tool was packaged into user-friendly software accessible through any web browser. The interface can accommodate users of all skill levels through its beginner-friendly features and straightforward layout. Additionally, the system was seamlessly integrated into ARDOT's existing databases, with options for manual data uploads to ensure flexibility in usage. To support ease of adoption, a comprehensive user guide was created, providing step-by-step instructions on navigating the interface and utilizing the software's various functionalities. The reporting system was designed to meet the diverse needs of engineers and other users, offering PDF export options for quick reference and Excel output for deeper analysis and customization.

Although the current system performs effectively, there is significant potential to adopt more sophisticated approaches that could surpass the accuracy and capabilities of the existing multivariate regression models. Particularly, machine learning models can handle complex datasets and generate more precise predictions. However, implementing these models would require a substantially larger volume of data than what is currently available within the agency. If adopted, machine learning techniques could be seamlessly integrated into various stages of the system workflow, including total man-hour forecasting, job distribution models, and final staff counts for each RE office. Additionally, more advanced techniques, such as deep learning models, offer the potential to further enhance prediction accuracy, particularly if sufficient high-quality data becomes available to properly train these complex models. With proper data infrastructure and collection strategies, these cutting-edge methods could elevate the system to a new level of forecasting precision.

Further research into the factors influencing workforce requirements revealed significant gaps in the available project data, which are crucial for accurate forecast planning. Notably, important indicators such as using CCEI consultants and a complexity metric that accounts for project difficulty, irrespective of its classified work type, were missing from the current dataset. These factors play a key role in determining the workforce needed for each project; hence, their absence limits the model's ability to produce highly accurate forecasts. Tracking such data in future projects would enable the development of more robust models with greater variability, ultimately resulting in more precise workforce estimates. Implementing a system that captures these critical factors, along with developing an in-house complexity ranking framework to assess and categorize future projects, is recommended. This would ensure a more comprehensive dataset and pave the way for more reliable forecasting models.

For future work, ARDOT should prioritize developing more comprehensive data tracking systems capable of generating a rich historical dataset. This extended history would enable the integration of more sophisticated models, such as neural networks and time series models, for forecasting purposes. These advanced models can provide deeper insights and more accurate predictions, but they require a larger, more detailed dataset to be effective. Additionally, creating a complexity index, a key factor known to significantly influence workforce requirements, should be emphasized. This complexity metric could be integrated into future forecasting tools to enhance their precision and adaptability. While the current system is designed for easy maintenance with the gradual addition of historical data, it is essential to actively maintain the system and explore the use of new variables, whether through updated multivariate regression models or more complex alternatives. Moreover, the software solution itself could be expanded to include additional functionalities that streamline workflows and integrate more effectively with other ARDOT processes related to workforce planning, ensuring the system remains scalable and future-proof.

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