International Journal of Engineering Science Invention
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 5 Issue 10|| October 2016 || PP. 37-48

Application and Results of a Skilled Labor Demand Forecast Model for the US Construction Industry

Stephanie C. Vereen[1], William Rasdorf[2], Joseph E. Hummer[3]
[1]*Civil, Construction, and Environmental Engineering, University of Alabama, United States*
[2]*Civil, Construction, and Environmental Engineering, North Carolina State University, United States*
[3]*North Carolina Department of Transportation, Raleigh, North Carolina, United States*

Abstract: *The construction industry is heavily reliant upon skilled labor. Forecasts of skilled labor demand for the construction industry are important to ensuring a well-trained and adequately staffed workforce. A labor demand forecast model for skilled workers in the United States construction industry has beendeveloped and successfully validated. Potential future trends for each independent model variablewere developed and then used to generate multiple labor demand forecast scenarios for the US construction industry through 2022. This paper presents both the trends and the results of these forecasts. The most likely forecast indicatesa need of 5.3 to 6.3 million skilled laborers in the construction industry by 2022, an increase of at least 23% over the 4.3 million skilled workers employed in 2012. With these results, construction industry stakeholders, including managers, employment policy makers, practitioners, owners, researchers, training and continuing education providers, and government agencies can be proactive in their planning and policy making as it relates to ensuring an adequate futureskilled construction labor force.*

Keywords: *construction industry, construction labor, forecast modeling, labor forecasting, skilled labor demand*

I. Introduction

The United States (US) construction industry faces a variety of challenges related to maintaining an adequate skilled labor force. These challenges include the mass exodus of the baby boom generation from the workforce beginning in 2012, the declining interest in skilled trades among school aged persons, and the loss of skilled workers to other industries due to unemployment in the construction industry[1, 2, 3]. In September 2012, *Engineering News Record* reported that "labor shortages are a potential cost threat once recovery kicks in" [4]. Also in 2012, FMI reported that the Associated Builders and Contractors professional organization estimated a gap of 500,000 craft jobs in America and that there was "a very slow pipeline of new recruits to fill them" [5].

As economic recovery continues following the recession ending in June 2009, industries other than construction will be recovering as well. Employers of skilled construction labor will have to compete with other industries for workers. "The oil and gas boom also has pulled many craft laborers away from traditional construction projects" [4]. Welders, for example, may transfer from industrial construction to oil field work sites. "Hence, employment planning and predicting the attributes of the construction [labor] market becomes a critical issue for the recovery of the wider economy" [6].

Industries such as power, petroleum and petrochemical, green building, and healthcare are all expected to grow significantly through 2020 and beyond. However, "the growth prospects for output and employment in the construction industry are [also] strong, so this is the most opportune and critical time to strengthen workforce development efforts in order to stay ahead of the curve" [7].

"Manpower forecast[ing] focuses on the expected quantity of jobs to be available and nature of requirements in the future" [8]. When examining the relevance of employment planning to the construction industry, Briscoe and Wilson note "forecasts provide a crucial foundation and framework for any planning exercise" [9].

"[Labor] resources are invaluable assets in the construction industry. Nurturing a quality workforce and promoting stable employment for construction personnel have often been advocated as part and parcel of an industrial policy. Yet the future [labor] market of the industry is always uncertain, and there is a need for estimating future [labor] market conditions as an aid to policy formulation and implementation." [6].

Forecasting skilled construction labor demand for the US construction industry, hereafter referred to as *labor demand*, is immensely important to a variety of industry stakeholders, including practitioners, owners, researchers, continuing education providers, government agencies, managers, and employment policy makers. Forecasting supports labor planning activities and informs construction industry stakeholders of what people and skills are needed, at what point in time they are needed, and in what quantities."Human capital is the foremost asset of any construction company, making placing the right people in the right positions an imperative for success" [9].

Stakeholders can use labor demand forecasts as metrics against which to compare their goals, objectives, and planning effort successesin workforce related areas such astraining and retention programs and policies. When these groups are able to reasonably forecast future changes and demands in labor markets, they can better assist workers, trainers, and educators with planning needs [11]. Maloney includes 'availability of a skilled workforce' in a list of important issues that should be addressed by construction organizations when developing labor planning strategies [12]. Briscoe and Wilson note that labor demand forecasting presents "training providers and other employment policy makers with information on the [labor] market environment that they may face, clarifying past trends and identifying new ones" [9].

Objective

A model to forecast skilled labor demand for the US construction industry was previously developed[13]. Material prices, construction output, productivity, and real wage were established as the independent model variables.

The objective of the current work (reported herein) was to utilize the model to develop potential trends for the future values of the models' independent variables and then input various combinations of thesevalues into the modelto create multiple labor demand forecast scenarios. "In addition to being used to predict trends in [labor] resources, employment forecasting models can also be used to examine alternative assumptions within the model framework, with the opportunity to examine different scenarios" [14]

Forecasting trends for independent variables and specific economic conditions can be difficult. "It is difficult for models that are based on projections of productivity, interest rates, and overall output to predict manpower needs; this is because of the difficulty in accurately forecasting economic activity and technological and commercial changes"[15]. What if the material prices increase? What if productivity declines? In 2008, Richardson and Tan wondered how policy makers could "best manage the irreducible uncertainty about the shape of future skill requirements" and whether "the best examples of model-based forecasting of the demand for skills provide an adequate basis for planning" as they relate to vocational and educational training, both initial and continual [16]. This paper attempts to overcome those difficulties and provide both accurate and useful projections.

The independent variables involved in labor forecasting cannot be controlled, do not have long leads, and are not very easy to forecast[17]. However, by developingdifferent potential trends for each independent variable,we can input various combinations and then evaluate and comparethe results of multiple forecast scenarios. "A sophisticated employment forecasting model can yield benefits beyond a single set of projections for use in planning training. Explicit alternative assumptions can be examined within the model framework and alternative scenarios can be explored"[9].Multiple forecast scenarios allow for anticipation and speculationaboutfuture labor demand. They prompt proactive analysis and planning by construction industry stakeholders.

II. Literature Review

In 1993, Briscoe and Wilson presented a study of labor demand forecasting, including characteristics for an employment forecast model, an assessment of data sources available to serve the model, the model, and other study related topics[9].They concluded that total employment in the UK construction industrycould be determined by a set of explanatory variables. They determined those variables to be output, real wage, and interest rate.

Briscoe and Wilson conducted a sensitivity analysis with their model by creating a series of simulations, or scenarios, and then assessing the impact the explanatory variables had on future employment in the UK construction industry. For example, one simulation involved reducing UK interest rates by 1 percentage point. For this scenario, in year 1, construction output would be 0.72 percent higher (compared with a base forecast) and in Year 10, it would be 0.81 percent higher than the base. Additionally, the Briscoe and Wilson study looked at sub-models of specific occupations, geographic regions, and region by occupations.

Briscoe and Wilson also analyzed the relationship of labor supply to labor demand.The results of their study included demand forecasts at an aggregated national level, and also atthe regional and occupational levels. They noted that their forecast model could be updated and improved with better data collection and sources and as feedback from users and planners was obtained and incorporated.

One of the earliest forecasts of construction labor demand was by Rosenfeld and Warszawskifor the Israeli construction industry [18]. They developed a methodology for forecasting construction labor demand for various skills and concluded their method could be applied to similar data in other countries. They projected demand needs and compared those values to the existing supply of labor. Their assessment resulted in the identification of a potential labor shortage. They concluded that skilled labor demand forecasting could then assist with the mitigation of a potential shortage by encouraging training programs or "labor-saving industrialized methods" [18].

In 2005, Wong, et al used the Box-Jenkins approach to develop an Autoregressive Integrated Moving Average (ARIMA) model to analyze and forecast construction labor market variablesfor Hong Kong [6]. They determined that theirmodel could be used to provide benchmark estimates for further analysis of the construction labor market and that the projections could offer valuable information and early signals to training providers and employment policy makers. They noted that "if employment forecasts could be made available to provide advance warning of like shortfalls, then training providers would be able to boost the supply skills and thereby mitigate some damaging effects of shortage" [6]. Wong et al developed and successfully validated several models. They concluded that their models could be used to "provide benchmark estimates for further analysis of the construction [labor] market." Although the models were only deemed to be reliable in the short run, they were still considered to be valuable tools for alerting training providers and employment policy makers of impending labor market trends for the Hong Kong construction industry.

Wonget al later used another modeling technique, vector error correction modeling, to create a model to forecast manpower demand for the Hong Kong construction industry[19]. Using it, they concluded that construction output and labor productivity were the most important factors to determining future construction manpower demand. Their results suggested that the proposed model could be used to produce medium-term forecasts of manpower demand.

Other researchers have produced models to create labor forecasts at the project level. Bell and Brandenburgcreated a model that was able to forecast project level manpower requirements for transportation projects[20]. Chan et al used the number of workers and project costs to establish multipliers that could be used to determine project labor demand by occupation [15].

Stillothers have presented results and validations of successful forecast models and modeling methodologies and then generated one particularforecast scenario. Agapiou et al created a supply forecast model focusing on craft trainee entrants to the UK construction industry [14]. Wage and output were deemed to be factors affecting an entrants' decision to train for construction jobs. Ho successfully utilized the gray model method to forecast construction labor demand with limited data [21].What sets this paper apart, however,is that it presents the results of industry level labor demand forecasts and also presents the results of multiple forecast scenarios.

The US Bureau of Labor Statistics (BLS) publishes projections of overall industry employment and output every two years. Each projection anticipates changes in employment and output for a 10-year period into the future and also recaps actual changes over the previous 10-year period[22]. The projections published in 2012 reported that the construction industry had experienced a -2.0% annual downward rate of change from 2000 to 2010 and that a 2.9% annual upward rate of change was projected for 2010 to 2020 [22]. This reflects movement from approximately 6.8 million jobs in 2000, down to 5.5 million jobs in 2010, and back up to 7.4 million jobs in 2020. The BLS is one of (if not) the most well respected and validated sources of data on all industries and occupations in the US. However, their projections represent aggregate data for the entire construction industry, regardless of skill. Also, the BLS always presents projections over a 10-year range, not the more finely grained monthly or yearly patterns that many analysts desire.

Our review of the literature shows that, other than the biennial BLS projections, no independent researchers have exercised a skilled labor demand forecast model beyond validation. Non-proprietary industry level forecast scenarios are simply not readily available. This paper fills that void.

III. Methodology

This research sought to create forecast scenarios for skilled labor demand based on potential future trends of the independent variables by using a new labor demand forecast model. Potential trends for each independent variablewere based on its historical trends. Potential combinations of the independent variables were input in the model resulting in labor demand forecast scenarios. This research analyzed four specific categories of labor demand forecast scenarios as well as the comprehensive results of all possible scenarios. The results are presented herein.

The following sections give a brief overview of the model, describe the process for calculating the potential trends for each independent variable, and present the results of the forecast scenarios. Finally, potential implications and benefits of the model results are assessed. Specifically, suggestions are provided for stakeholders in the construction industry (managers, employment policy makers, practitioners, owners, researchers, training and continuing education providers, and government agencies) so that they can be prepared for the broad range of future labor demand possibilities they might encounter.

The Model

The model was based on existing data collected from 1990 through 2011. The last two years ofdata, 2010 and 2011, were withheld from the model development for validation purposes. The forecast scenarios were generated for a future 11 year period, beginning in 2012 (where the model data set ended) and continuing through 2022.

Vector autoregression (VAR) modeling was used to develop the forecast modelfor labor demand. Xu and Moon applied a similar modeling technique to generate accurate forecasts of the construction cost index [23]. "Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model" [24]. The resulting model, which was based on the model described earlier by Wong, Chan, and Chiang for the Hong Kong construction industry,can be expressed as:

LD_t = -0.08948 + 0.94315 (log LD_{t-1}) + 0.03304(log MP_{t-1}) + 0.03515 (log O_{t-1})+ 0.79475 (diff log LP_{t-1}) – 0.54633 (diff log W_{t-1}) -0.04031 ($c_{1,t}$)+ 0.00903 ($s_{1,t}$) –0.01015($c_{2,t}$)– 0.01715 ($s_{2,t}$)t=1,,T(1)

where LD is labor demand (workers), MP is material price (unitless index), O is construction output (SF), LP is labor productivity (unitless index), and W is real wage (US dollars per hour) [19]. The model coefficients are associated with U.S. customary units only and are not transferable to metric. T is equal to the 216 months of data from January 1990 to December 2009 on which the model was calibrated. All variables were statistically significant at the 95-percent level.
The terms c_1, c_2, s_1, and s_2 are trigonometric variables to adjust for the semi-annual seasonal nature of the construction industry represented by the following set of equations:

$c_1 = \cos(\pi kt/L)$ (2)
$s_1 = \sin(\pi kt/L)$
$c_2 = \cos(2\pi kt/L)$
$s_2 = \sin(2\pi kt/L)$

In addition to the use of trigonometric variables, which adjusted for seasonality in the data, additional analysis of the variables and validation of the model revealed that some log and differencing transformations were necessary to adjust for the variance in the data over time and these transformations produce more accurate model results. Thus, log transformed values for labor demand, material price, and construction output and differenced log values for productivity and real wage were used herein.
It is important to note that VAR modeling considers the time series nature of all of the input variables (labor demand and the four independent variables) together and then forecasts the entire model forward simultaneously. VAR modeling creates a separate equation for each variable, represented by a *k x 1* vector, where *k* is equal to the total number of variables. For this research *k* was equal to 5. The previously stated Equation 1 is 1 of a totalof 5 equations generated during the VAR modeling process, all of which are intended to forecast future values of the independent variables simultaneously with the independent variable.
Although VAR presents additional equations that can be used to develop future values for the independent variables, there is only one output (potential trend) and it based solely on the model. This research develops multiple potential data trends for the independent variables taking into account real world labor market, economic, and industry conditions. The intention was to develop intelligent and logical trends that can then be used to create realistic and usable forecast scenarios.
The model expressed in Equation 1 was validated to a mean average percent error (MAPE) value of 1.14 and a Theil's U value of 0.38, both of which are within acceptable ranges of their respective evaluation methods, especially considering the unusual economic conditions during those years.

IV. Potential Trends For The Independent Variables

Forecastingfuture values of the independent variables (material price, output, productivity, and real wage) was not an inherent objective of the research. However,potential future trends of thoseindependent variables' values are needed to forecast future labor demand scenarios. The method for calculating the potential trends is presented here.
Threepotential trends were created for each variable based on the future values of the variable changing at either a low,medium,or high rate. The magnitude of change for each rate was established by evaluating the historical percent changes in the data sets over 10-year spans from 1990 to 2011. A total of twelve 10-year spans were created. The first span was 1990 through 2000, the second span was 1991 through 2001, and the subsequent spans continued through to the twelfth span from 2001 to 2011.
From the 12 values for each variable, the lowestand highest percent change values were selected to establish the low and high potential trends and the median percent change value was selected to establish the medium potential trend. (The data series for each variable consisted of monthly data, so the average annual value was used to determine the percent change values.)For some variables,extreme outliers among the 12 percent change values were discarded prior to selecting the lowest, median, and highest values.

The following sections discuss the results of the low, medium, and high potential trends for each independent variable using this methodology. The method for establishing the potential trends for construction output differed slightly due to the cyclical nature of the data and is discussed hereafter.

Material Price

Material price data were collected from the Material Price Index (MPI) published monthly by the *Engineering News Record* (ENR) periodical[25].MPI is based on the cost to purchase a hypothetical package of steel, cement, and lumber. Although material price has experienced short periods of decline in the past(as shown by the historical data line in Fig. 1, e.g. 2002) the overall data pattern from 1990 to 2011 is increasing. Also, theMPIis a value that measures the relative level of material price from month to month. Upward movement in the level represents inflation. The probability of deflation in the US economy over any extended period of time is very low. Thus, a reasonable assumption is that the overall MPIwill increase in the future.

The lowest, median, and highest percent change values for material price were 11, 22, and 28, respectively. Fig. 1 shows the low, medium, and high potential trends for material price, based on these percent change values. The historical data for material price are also presented in Fig. 1.

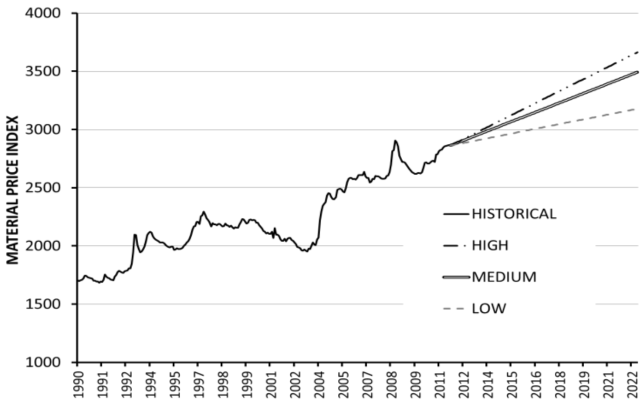

Figure 1: Material Price Index Historical Data (1990 – 2011) andPotential Trends (2012 – 2022)

Productivity

Productivity data werederived from a new metric utilizing RS Means Building Construction Cost Data [13]. According to this metric, construction productivity has experienced a steady decline over time. Similar to material price, productivity is an index of values that measures the relative level of productivity from month to month. The lowest, median, and highest percent change values for productivity were determined to be 5, 11, and 23, respectively. Fig. 2 shows the resulting low, medium, and high potential trends for productivity, as well as the historical data.

Real Wage

Real wage data were collected from the National Employment, Hours, and Earning data published as part of the BLS CES [26]. The trend for real wage from 1990 to 2011, as shown in Fig. 3, was that it increased linearly over time, due primarily to inflation. Several of the other variables have more sporadic and less linear trends and fluctuations; however, real wage exhibits a clear and relatively linear trend.

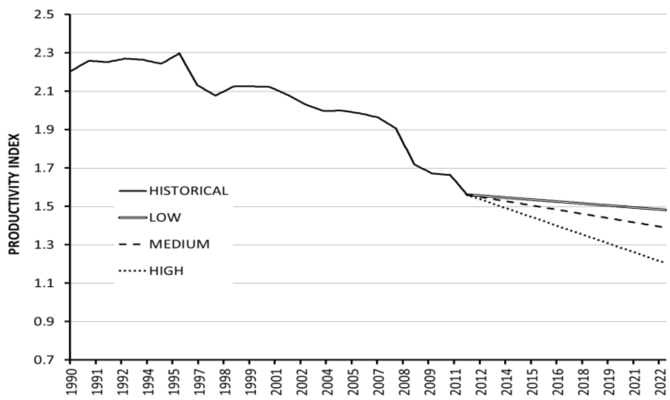

Figure 2: Productivity Index Historical Data (1990 – 2011) and Potential Trends (2012 – 2022)

The lowest, median, and highest percent change values for real wage were 30, 34, and 37, respectively. This range between the percent change values results in respective low, medium, and high hourly wage valuesin 2022 of $29.75,$32.13, and $34.51, respectively.Fig. 3 shows the low, medium, and high potential trends for real wage, based on the percent change values.

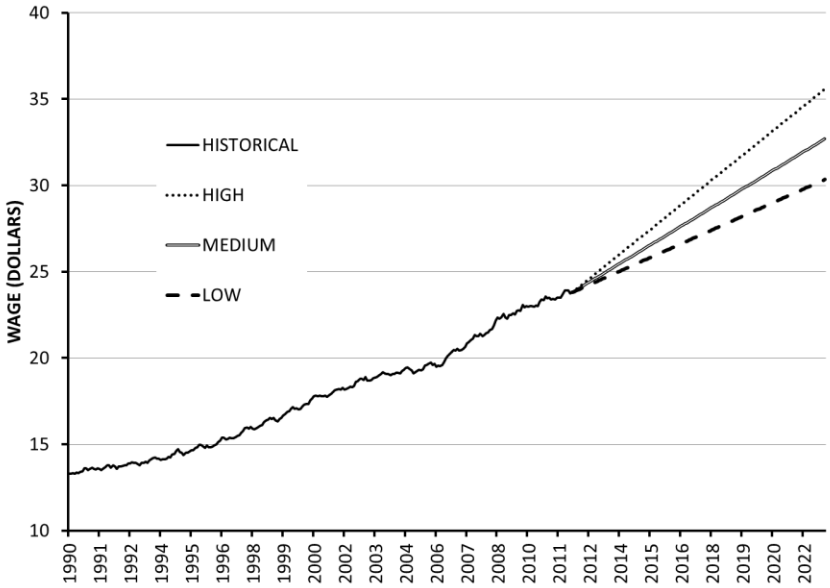

Figure 3: Real Wage Historical Data (1990 – 2011) and Potential Trends (2012 – 2022)

Construction Output

Square footage data for construction output were derived using construction spending values published by the US Census Bureau and square footage cost data published in RS Means Building Construction Cost Data annuals. Construction industry output data are cyclical and seasonal in nature as shown in Fig.4.

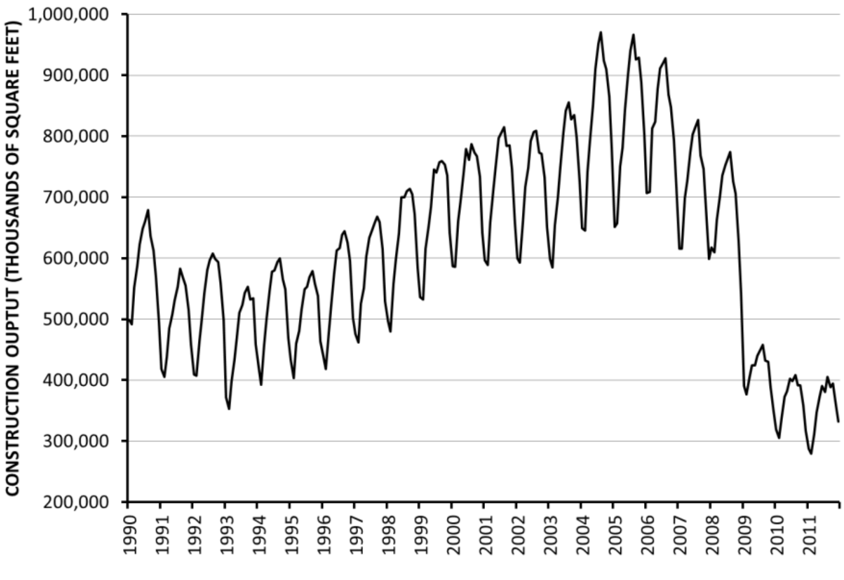

Figure 4: Monthly Construction Output Data (1990 – 2011)

Because of the cyclical nature of construction output data, the percent change method discussed previously was not suitable because the potential future trends would not be linear. Therefore, potential trends were derived for the lowest and highest data points in the cycle which occur in January and August, respectively using percentiles. The assumption we used was that construction output in the US will never be higher than the boom years of 2004 - 2005 (approximately 970 million SF)nor lower than the lean years of 2010 - 2011 (approximately 280 million SF)

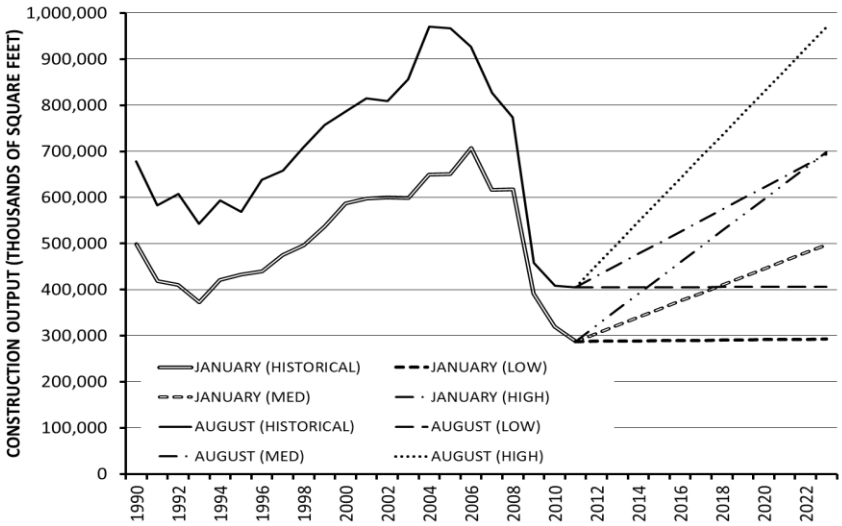

Figure 5: Construction Output Historical Data (1990 – 2011) & Potential Trends (2012 – 2022)

Percentiles were calculated for January and August; 5th percentile for the low potential trend, 50th for medium, and 95th for high. For example, the 50th percentile of historical construction output data in January (1990 - 2011) was approximately 497 million SF per month. Thus the medium potential trend is based on the value of construction output reaching that value by January 2022. The assumption is that, by the year 2022, construction output in the US will fall within the 5th and 95th range established from the historical data set.

Once potential trends were created for January and August, historical average percent changes between those months were used to calculate the corresponding values for the remaining 10 months. Fig. 5 shows the low, medium, and high potential trends for January and August construction output through 2022.

V. Forecast Scenarios And Results

Based on different combinations of the potential trends for the values of each variable there are many labor demand forecast scenarios that could be produced.The results of four of the most interesting forecast scenarios are categorized and presented here.

1) Each of the independent variables experiences an extreme change independently (e.g. material prices rising high, while all other variables follow their medium potential trend).
2) All of the independent variables experience the same magnitude of change simultaneously (e.g. all variables experience low potential trend).
3) Independent variables behave differently in the future than they have trended in the past (e.g. alternate potential trend).
4) Extremes analysis, which is an assessment of individual values of each independent variables thatresult in labor demand reaching an extreme high or extreme low value.

In addition to these specific sets of scenarios, all possible combinations of the low, medium, and high potential trends were developed.

The methodology for creating the forecast scenarios was to enter the values of the potential trends of each independent variable into the previously developed forecast model to produce labor demand forecasts. The development of the potential trends for each variable was discussed previously in this paper. The following sections present and analyze the resulting labor demand forecasts.

Each Variable Examined Independently

The first category of forecast scenarios evaluated the outcome if one variable trended higher and all other variables followed their medium potential trend. The resulting forecast scenarios for labor demand are shown in Fig. 6. Increasing wages and decreasingproductivity to their high potential trends produce almost the same result, a peak of about 6.3 million workers by 2022 (these two lines overlay each other). Increasing material price results in a slightly higher labor demand, peaking at 6.5 million workers by 2022. Increasing output to its highest potential trend (while holding material price and wage increase and productivity decrease along their medium potential trends) produces the highest future values for labor demand over time, a peak of 7.6 million workers by 2022. Thus it can be concluded that output has the greatest effect on labor demand of the variables in the model; as output increases, so does labor demand. We now have a model to quantify these interactions.

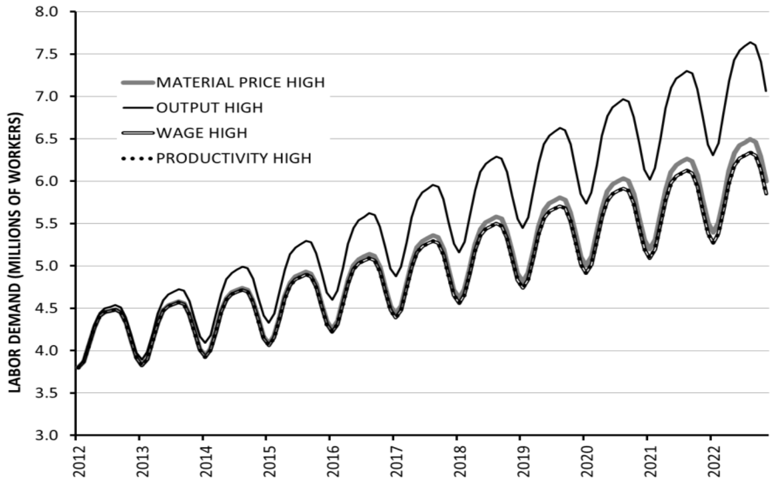

Figure 6: Category 1 Labor Demand Forecast Scenarios

All Variables Trend at the Same Magnitude

The second category of forecast scenarios evaluated the outcome if all of the variables followedtrends of the same magnitude. Fig. 7 shows the results of the forecast scenarios whereeach variable experienced either all low, all medium, or all high potential trends simultaneously.

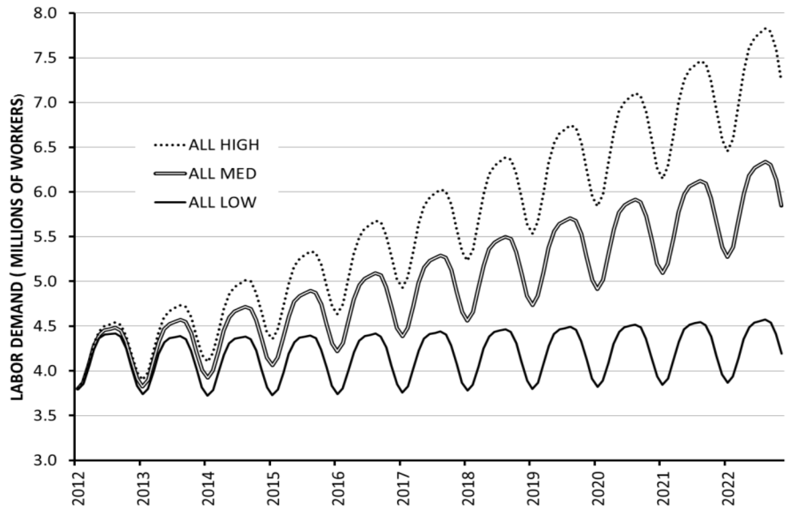

Figure 7: Category 2 Forecast Scenarios

If the all low and all high forecast scenariosrepresent reasonable limits on the future of the US construction industry, Fig. 7 is helpful in showing the broadest potential range of employment in 2022. If all of the variables follow their low trend, skilled labor demand will barely increase from its 2011 levels, remaining steadyin the 4 million worker range. If all of the variables follow their medium trends, skilled labor demand increases steadily to about 6.25 million workers in the peak summer season of 2022. If all of the variables follow their high trend, a skilled labor demand of almost 8 million workerswould be attained bythe peak season in 2022. This high trend scenario is unlikely as it would involve a significant increase in material prices, construction output, and wages coupled with adecrease in labor productivity. Further evaluation of the possibility and circumstances involved in reaching extremely high labor demand values in the future and an overall assessment of all potential combinations are discussed in later sections.

Independent Variable Behaves Differently than Historically

The third category of forecast scenarios evaluated the material price variable trending differently in the future than it has in the past. What if in the future, for example, innovative new materials are introduced that increase output and decreasematerial prices, thereby shifting the historically linearly increasing trend of material price to decreasing? Category 3 presents an alternate potential trend to develop an alternate forecast scenario for exactly this example of material price changes.

Fig. 1 showed that material price experienced some periods of linear decline.It is well known that material prices are constantly subject to price fluctuations due to factors such as scarcity or abundance of raw materials, turmoil in oil-producing countries, and demand, all of which maycause material prices to fluctuate in the future.
To evaluate such a possibility, ahigh decreasing potential trend was developed for material price.Thisalternate potential trendmirrored the high increasing potential trend shown in Fig. 1, but was opposite in magnitude. The resulting labor demand scenario is shown in Fig. 8 which, for comparison, also shows the forecast scenario where all the variables increase at their medium potential trend.
Traditional economic theory suggests that a decrease in material price would in turn decrease the cost of output which would lead to an increase in quantity of output (owner's want to build when they can get more for their money). This is known as output effect. But if material and labor were interchangeable, such that a company could use one instead of another, then cheaper materials would cause a firm to use more material and fewer workers, thus decreasing labor demand. This is known as the substitution effect [27]. Fig. 8 shows that the model predicts a sizeable substitution effect, in that a large decrease in material prices over time results in a large decrease in labor demand compared to what it would have been with medium material price increases. This assumes that labor and material can to some degree replace one another. Also, it is often the case that both effects occur to some degree and their net effect is then uncertain [27].

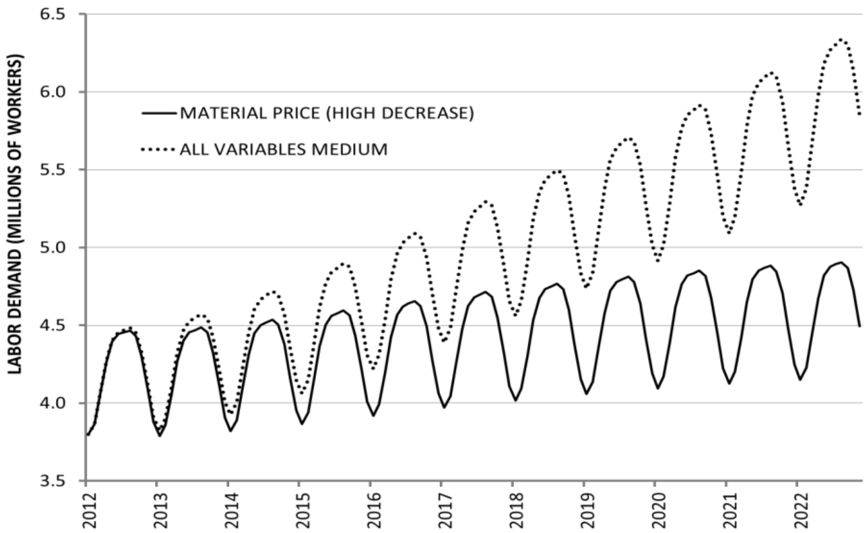

Figure 8: Labor Demand Forecast Scenario Using Alternate Potential Trend for Material Price

Extreme Value Analysis

The first three categories of labor demand scenario forecasts focused on what would happen to future labor demand based on various combinations of potential trends for the independent variables. We were also interested in reversing the problem and investigating combinations of potential trendsthat would cause labor demand to reach extreme values in the future. If labor demand were projected to meet or exceed 8,000,000, for example, a substantial effort towards preparing enough workers to meet this considerable demand would be necessary. Alternately, if future labor demand were to decline significantly towards 3,000,000 workers, a surplus of skilled workers would be likely and preparations should be made for them to re-trainfor other industries.
Historically, the peak of the annual labor demand cycle ranged from 3.7 million workers following the economic recession in the early 1990's to a high of about 6.2 million workers in 2006, just prior to the economic recession that ended in 2009. The overall labor demand trend increased from 1990 to 2011, except for periods immediately following economic recessions.Fig. 7 showed labor demand beginning to reach an extreme value of almost 8 million workers by 2023. This scenario would occur if all of the independent variables increased at their highest anticipated rates.
Table 1 presents the data for each independent variable that would create these two extreme low and high scenarios. The first column lists the dependent variable and each independent variable. The second and third columns give the lowest and highest historical values for labor demand, which occurred in February 2011 and August 2006, respectively. The fourth and fifth column present future extreme lowand high labor demand values and the corresponding independent variable values. Forecasted values using VAR modeling are based on data from the previous month. Thus the future independent variable values noted in Table 1are those of the month immediately precedingthe future labor demand values.

Construction output has the greatest impact of any variable. During a recession, wages probably become more of a dependent variable than an independent variable; as labor demand decreases and there is an overage of skilled labor, workers are willing to accept a lower wage to remain competitive in a tight labor market.
Productivity does not have much of an effect. Again, the dependent trend of productivity is that more workers are producing less output. During a recession, companies and firms may retain more workers than necessary in order to sustain and maintain their most valued and skilled workers. Thus industry level productivity appears to decrease as more workers are producing the same amount of relative output out of necessity. It is unlikely that future construction output would ever be lower than the historical low of 279 million SF, thus the extreme low scenario used this as a threshold for the value of future construction output to create the extreme low scenario.

Table 1: Possible Extreme Values of Labor Demand in the Future

	Past - Actual		**Future Extreme Low**	**Future Extreme High**
	FEB 2011	**AUG 2006**		
Labor Demand (Number of Workers)	3,738,000	6,236,000	2,810,000	8,000,000
Material Price (Index)	2723	2610	2760	4000
Construction Output (Millions of SF)	279	927	279	1,600
Productivity (Index)	1.66	1.97	1.27	1.20
Real Wage (US Dollars per Hour)	23.40	20.20	27.20	35.30

The future extreme high resulting from all of the forecast scenarioswas approximately 7.8 million workers, which would presumably occur in September 2022 when construction output and material prices experience their highest levels. We tried to push beyond that and find scenarios in whichlabor demand exceeded 8 million workers by 2022. The most significant finding of this exercise was that, for labor demand to exceed 8 million people by 2022, construction output would have to increase to 1.6 billion SF per month. That is 78% higher than the highest construction output recorded to this point thus, is very unlikely that labor demand in the construction industry will exceed 8,000,000 workers by December 2022.

Overall Analysis
In addition to the special categories presented in the previous sections, forecasts were created using all possible combinations of the potential trends for each variable.Fig.9 shows that in the summer of 2022 the average of the 81 forecasted values (four variables each at three levels totaling 81 combinations) would be 6.2 million skilled workers.

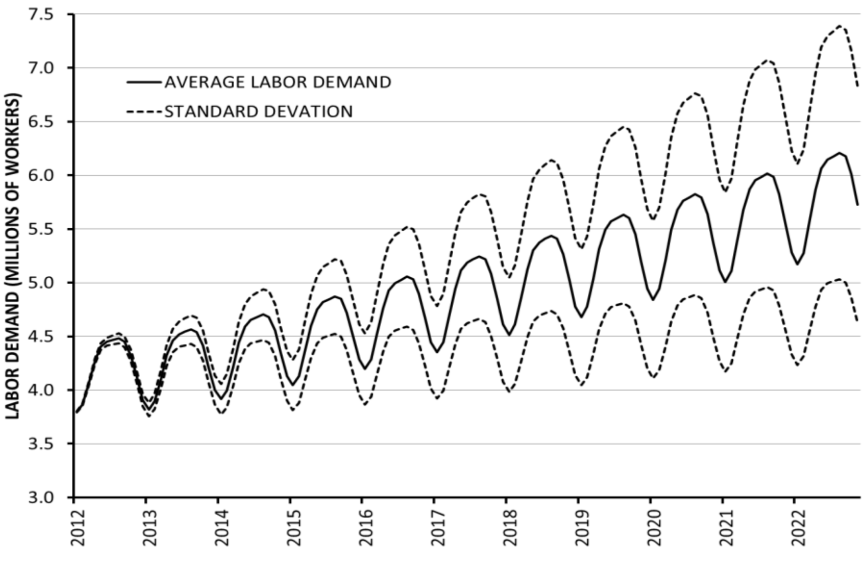

Figure 9: Average Monthly Values Standard Deviation of Forecasted Labor Demand

The standard deviation around that average is 1.1 million workers resulting in a low of 5.1 and a high of 7.3 million workers in 2022. The standard deviation around the average starts low, at about 6,000 workers in 2012, and gradually increases as time passes.

VI. Conclusions

Construction industry stakeholders need to be able to plan and prepare for the future skilled construction labor workforce. Use of a valid and reliable forecast model is critical to the development of and planning for an adequate skilled labor force. Thisresearch focused on the application of a new labor demand forecast model to generate forecasts for the number of skilled laborers that may be needed in the future, given various potential trends of the independent variables in the model. The results provide insights into the effects of the independent variables on future construction industry labor demand.

It was determined that demand would only reach an extreme low (less than 3 million) if construction output were severely diminished. This is very unlikely to occur. The construction industry, in tandem with the overall US economy, is still making strides in recovering from the economic recession that ended in December 2009, and recovery signals a positive trajectory for construction output in the short and long term future. The resurgence of construction on power plants, alternative sources of energy,population growth-related structures in the US (schools, healthcare facilities, public services), and the continuing need to improve and expand all aspects of infrastructure systems in the US, all signal that continual increases in construction output and labor demand are very likely.It is also very unlikely that labor demand would reach an extreme high, exceeding 8 million workers, by 2022. The conditions necessary to require such a robust workforce are not likely to occur over the next 10 years, especially if a new recession were to occur and detract from future increases.

From the results, it can be concluded that construction output is the most important independent variable influencing future labor demand. Although material price, productivity, and wages are influential, fluctuations in construction output (among the different forecast scenarios) produced the greatest impact on labor demand.

The results presented herein were derived from a model that is able to reasonablyproduce medium-term (10 years) forecasts for skilled labor demand in the construction industry. The forecasts can be used by US construction industry stakeholders to adequately plan and prepare for future labor needs. Future labor demand may fall into a wide range of values; however, it is most likely that labor demand will trend according to the average value of all possible scenarios as demonstrated in Fig.9. This represents a demand range of between 5.3 and 6.3 million skilled workers by 2022. Between 2011 and 2013, skilled labor demand in the US construction industry ranged from 3.7 to 4.4 million [26]. This indicates a likely need to increase the skilled labor workforce for construction by 1.3 to 3.0 million workers by 2022. That would mean 145,000 to 330,000 new workers would need to be added annually to meet the demand. This projection does not take into account workers lost due to attrition. The year 2012 marked the beginning of a likely mass exodus of baby boom generation workers from the overall US workforce; a generation of workers will retire, and without replacement, demand for new hires will grow even more than anticipated by this model.

It is easy to disregard future labor demand needs and the potential that labor shortages could result from an inadequately trainedworkforce. August 2012 marked the 48^{th} consecutive month of double digit unemployment in the construction industry [4]. The construction industry is highly cyclic; so long term shortagesareoften concealed by short term declines. However, previous research and industry publications have suggested impending skilled labor shortages in the construction industry and these results further support this.

Labor demand forecast results are key inputs into decisions to be made about training, recruitment, continuing education, and retention needs for the construction industry. Skilled labor occupations require a range of training and education so there is often a delay between entering an occupation and becoming skilled in it. Having quantitative data about future labor demand needs can assist with more effective and accurate planning.

VII. Recommendations

This research provides a contribution in the area of labor demand forecasts in the US construction industry. The forecast scenarios developed in this study can benefit the construction industry and its stakeholders. Specifically, they can use the data and results in the following ways:

- Practitioners
  - plan for and provide company sponsored training and continuing education
  - plan to retain qualified workers during periods of slow work or during low demand seasons or acquire new workers during periods of high demand
- Owners
  - provide an awareness about increased labor costs
  - collaborate with industry on long term project planning (future construction output)
- Researchers
  - continue toanalyze skilled labor trends for the industry
  - update the model and forecasts as new data become available
- Training providers
  - expand training programs
  - increase recruiting efforts

- Government agenciesand policy-makers
  - implement policy to address skilled labor shortages
  - increase funding for skills training and continuing education programs

In addition to the specific recommendations offered to researchers in the above list, there is additional research that should be conducted to grow the body of knowledge related to construction industry skilled labor demand into the future.

- Develop a computer interface and underlying database that would allow for the generation of labor demand forecasts by selecting potential trends.
- Simulate the life cycle of skilled construction laborers for a better understanding of the flow of workers and the effects of attrition on labor demand.
- Evaluate the effects of exogenous variables (other than recession). This study focused on altering the endogenous variables of the model.
- Develop metrics to track actions and initiatives made by industry stakeholders to address skilled labor demand and measure the outcomes.

References

[1]. Construction Users Roundtable (CURT),*Confronting the Skilled Construction Workforce Shortage*, Report WP-401, 2004.
[2]. A. Heimbach, S. Hoover, N. Schubert, and N. Heir, Perspectives on Future Construction Labor Shortages*FMI Quarterly,*Issue 2,2006, 28 - 49.
[3]. C. Fiori, G. Brown, and K. Sadowski, What are the Best Practices for Skilled Labor Recruitment and Retention? It Depends Upon Whom You Ask,*Proc. 2nd Specialty Conference on Leadership and Management in Construction*, Grand Bahama Islands, Bahamas, 2006, 185 – 191.
[4]. Engineering News Record (ENR) (2012). “Labor Costs Inch Upward Despite High Unemployment,” McGraw-Hill Companies, Hightstown, NJ, September 24, 2012, *269(9)*, 47.
[5]. Fails Management Institute (FMI) (2012), Recovering the Lost Generation for the Construction Industry’s Future,*Technical Report*, FMI Corporation, Raleigh, NC.
[6]. J.M. Wong, A.P.C. Chan, and Y. H. Chiang, Time Series Forecasts of the Construction Labour Market in Hong Kong: The Box-Jenkins Approach, *Construction Management and Economics, 23(9),* 2006,979 - 991.
[7]. N. Dorman, Professionals in Demand: The Need for Qualified Skilled Workers is on the Rise,*The Cornerstone*, Fall 2011, National Center for Construction Education and Research (NCCER), Alachua, FL.
[8]. J.M.W. Wong, A.P.C. Chan, and Y.H. Chiang, A Critical Review of Forecasting Models to Predict Manpower Demand,*The Australian Journal of Construction Economics and Building,* Australian Institute of Quantity Surveyors, *4(242)*,2004, 43 – 56
[9]. Briscoe, G. and Wilson, R. (1993). *Employment Forecasting in the Construction Industry*. Avebury, Aldershot, United Kingdom.
[10]. E.M. Rojas, Identifying, Recruiting, and Retaining Quality Field Supervisors and Project Managers in the Electrical Construction Industry,*Journal of Management in Engineering, 29(4)*,424 – 434.
[11]. E. Willems, Interpreting Gaps in Manpower Forecasting Models.” *Labour*, *12(4)*, 1998,633 - 41.
[12]. W.F. Maloney, Strategic Planning for Human Resource Management in Construction,*Journal of Management in Engineering*, *13(3)*, 1997,49 – 56.
[13]. S. Vereen, W. Rasdorf andJ. Hummer, Development and Comparative Analysis of Construction Industry Labor Productivity Metrics.” *Journal of Construction Engineering and Management*, *142(7)*, 2016.
[14]. A. Agapiou, A. Price and R. McCaffer, Planning Future Construction Skill Requirements: Understanding Labour Resource Issues,*Construction Management and Economics,13(2),*1995, 149 - 161.
[15]. A.P.C. Chan, Y.H. Chiang, S.W.K.Mak, L.H.T. Choy, and J.M.W. Wong, Forecasting the Demand for Construction Skills in Hong Kong, *Construction Innovation,6*, 2006, 3 - 19.
[16]. S. Richardson and Y. Tan, Forecasting Future Demands: What we Can and Cannot Know, *Australian Bulletin of Labor,* National Institute of Labor Studies, *24(2)*,2008, 154 - 191.
[17]. P.G. Allen and R. Fildes, Econometric Forecasting, in J.S. Armstrong (Ed.), *Principles of Forecasting: A Handbook for Researchers and Practitioners*,(Norwell, MA: Kluwer Academic Publishers, 2001).
[18]. Y. Rosenfeld and A. Warszawski, Forecasting Methodology of National Demand for Construction Labour,*Construction Management and Economics, 11(1)*,1993, 18 - 29.
[19]. X.J. Xu, and S. Moon, Stochastic Forecast of Construction Cost Index Using a Cointegrated Vector Autoregression Model,*Journal of Management in Engineering,29(1)*, 2013 10 – 18.
[20]. L.C. Bell and S.G. Brandenburg, “Forecasting Construction Staffing for Transportation Agencies.” *Journal of Management in Engineering,19(3)*,2003, 116 - 120.
[21]. P.H.K. Ho, Forecasting Construction Manpower Demand by Gray Model, *Journal of Construction Engineering and Management, 136(12)*,2010, 1299 - 1305.
[22]. R. Henderson, R., Employment Outlook: 2010 – 2020; Industry Employment and Output Projections to 2020, Bureau of Labor Statistics Division of Industry Employment Projections, Office of Occupational Statistics and Employment Projections, Monthly Labor Review, January 2012, Washington, D.C.
[23]. J.M.W. Wong,A.P.C. Chan, Y.H. Chiang,Forecasting Construction Manpower Demand: A Vector Error Correction Model,*Building and Environment, 42(8)*,2007, 3030 - 3041.
[24]. E. Zivot,*Modeling Financial Time Series with S-Plus*(New York: Springer, 2006).
[25]. Engineering News Record (ENR), Construction Economics,*Materials Cost Index,* McGraw-Hill Companies, Hightstown, NJ., 1990-2011.
[26]. Bureau of Labor Statistics (BLS), Occupational Employment Statistics,*Employment, Hours, and Earnings from the Current Employment Statistics Survey (National),* <http://www.bls.gov/ces/data.htm>(Accessed 8/30/2013).
[27]. W.J. Wessels,*Economics,4th Edition*(Hauppauge, NY:Barrons, 2006).