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Dynamic Human Resource Predictive Model for Complex Organizations

Tachapon Saengsureepornchai
tsaengsu@utk.edu

To the Graduate Council:

I am submitting herewith a thesis written by Tachapon Saengsureepornchai entitled "Dynamic Human Resource Predictive Model for Complex Organizations." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial Engineering.

Rupy Sawhney, Major Professor

We have read this thesis and recommend its acceptance:

Joseph Wilck, Gregory A. Sedrick

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Dynamic Human Resource Predictive Model for Complex Organizations

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ABSTRACT

Every organization has to deal with planning of the appropriate level of human resources over time. The workforce is not always aligned with the requirements of the organization and it increases an organization’s budget. A literature review reveals that there is no model that can systematically predict accurate human resource required within a complex organization. To address this gap, a human resource predictive model was developed based on material requirements planning (MRP). This approach accounts for complexity in workforce planning and generalized it with a logistic regression model. The model estimates the employee turnover number and forecasts the expected remaining headcount for the next time period based on employee information such as; age, working year, salary, etc. Moreover, external variables and economic data can be utilized to adjust the estimated turnover probability. This model also suggests the possible internal workforce movement in case of in-house manpower imbalance.

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CHAPTER I

INTRODUCTION AND GENERAL INFORMATION

1.1 Introduction

In today's dynamic business environment, organizations often experience great stress when determining an appropriate level of their workforce.
An adequate workforce is critical to the smooth functioning of any organization. Thus, a systematic approach to monitor, manage and accurately estimate the correct number of employees is essential for the healthy functioning of the organization. The two most basic problems arising out of a misaligned workforce are overstaffing and its opposite, an insufficient workforce. The following sections discuss the relevance of these issues in detail.

1.1.1 Overstaffing

This section describes and illustrates the issue of overstaffing. The recent economic downturn has resulted in U.S. unemployment rates that increased dramatically from 4.5 percent in 2000 to 9.6 percent in 2010 (Statistics, 2010). Many organizations have opted to cut their nonessential workers in order to produce a quick, budget-saving response to the financial crisis. However, cutting nonessential workers presupposes that these organizations already had a chronic overstaffing problem, or they would not have been able to make the cuts; during favorable economic times, more and more employees had been hired, perhaps without management's explicit consciousness of the actual workforce demand. In fact, many authors have reported on overstaffing both in public and private organizations (Borcherding, Pommerehne, & Schneider, 1982; Clarke & Pitelis, 1993; Hart, Shleifer, & Vishny, 1997; Haskel & Szymanski, 1993).

Overstaffing in companies usually entails excessive human-capital costs along with the expense of providing the extra staff with facilities such as office spaces, parking space, and IT resources. Downsizing does indeed provide organizations with a quick way to reduce costs. However, a sudden reduction in workforce can cause indelible trauma to the morale of the workforce (Noer, 1993). It can also damage an organization's core ability to compete. (Trevor & Nyberg, 2008). For example, if an organization reduces headcount from an oversized workforce to a certain level without monitoring the turnover rate and workforce competence, the company's workforce may eventually prove inadequate (Cascio, 1993; Sturman, Trevor, Boudreau, & Gerhart, 2003).

1.1.2 Insufficient Workforce

This section describes the situation when organizations have an insufficient workforce. One problem with an inadequate workforce in some types of companies is late delivery. The costs associated with delivery delays are enormous and may, over time result in a loss of market share. Another example can be found in the U.S. health-care system, where there are continual risks of workforce shortage across the entire spectrum of the system, from nurses to primary physicians to highly trained surgeons. The number of general surgeons (who play a crucial role in the country's health-care system) has begun to drop in recent years, while the U.S. population as a whole has kept increasing (Kwakwa & Jonasson, 2001). As a result, more patients have to wait outside emergency rooms in the hospitals. This problem is apparent in such subspecialties as dermatological services. Multiple surveys have documented a stable undersupply of dermatological services since 1999 (Kimball & Resneck Jr, 2008) resulting in new patients having to wait an average of 33 days for an appointment.

The ability to systematically detect an oversized or undersized workforce based on dynamic workforce management system would make contemporary organizations more competitive.

1.2 Problem Statement

A 1993 Society for Human Resources Management (SHRM) survey found that six out of ten companies had no strategy for planning their workforce (Lavelle, 2007). In fact, organizations generally treat recruitment as a reactive event, responding to the need to fill either a new position or one that has been left open. This reactive approach will, over time, create a misalignment between the number of employees and the workforce requirement, especially when the process of hiring and training new employees requires large lead times. It is probable that a predictive model would alleviate this concern to some extent. Mobley et al. (1979) reviewed the studies of variables or factors that impact workforce withdrawal, but to date, no predictive model has been developed to help organizations manage their workforces. This leads to a precarious imbalance between organizational goals, budgets, employee morale, and overheads over the long term.

1.3 Conceptual Framework

The conceptual framework of this study, as shown in Figure 1, aims to provide a general approach to developing a Human Resource Predictive Model (HRPM). This framework is based on the logic used in Material Requirement Planning (MRP) systems for controlling physical inventory. This HRPM consists of two modules: Gross Workforce Demand (D) and Workforce Availability (HC’)

This study anticipates that a given organization has the ability to forecast the value of D (Gross Workforce Demand), based on the techniques shown below. This thesis will utilize the available data and apply it to the workforce-planning model to generate the predictions.

- Gross Workforce Demand (D): The techniques for determining “D” can be classified into six major categories (Ward, 1996):
    - Direct managerial input,
    - Best guess
    - Historical ratios
    - Process analysis
    - Statistical methods
    - Scenario analysis.
- Workforce Availability (HC’): The functioning of HC’ requires knowledge about the existing workforce (known information) and about workforce leaving (predicted information). It is important to enter accurate information about each component in order to enhance planning reliability. A literature review reveals that there is no strong evidence to recommend a predictive model of employee voluntary withdrawal. Therefore how can an organization predict employee turnover so as to balance organizational goals, budgets, employee morale, and overheads over the long term? This study focuses on the determination of an optimal approach to predicting voluntary withdrawal of workforce and hence to developing a systematic workforce planning model.

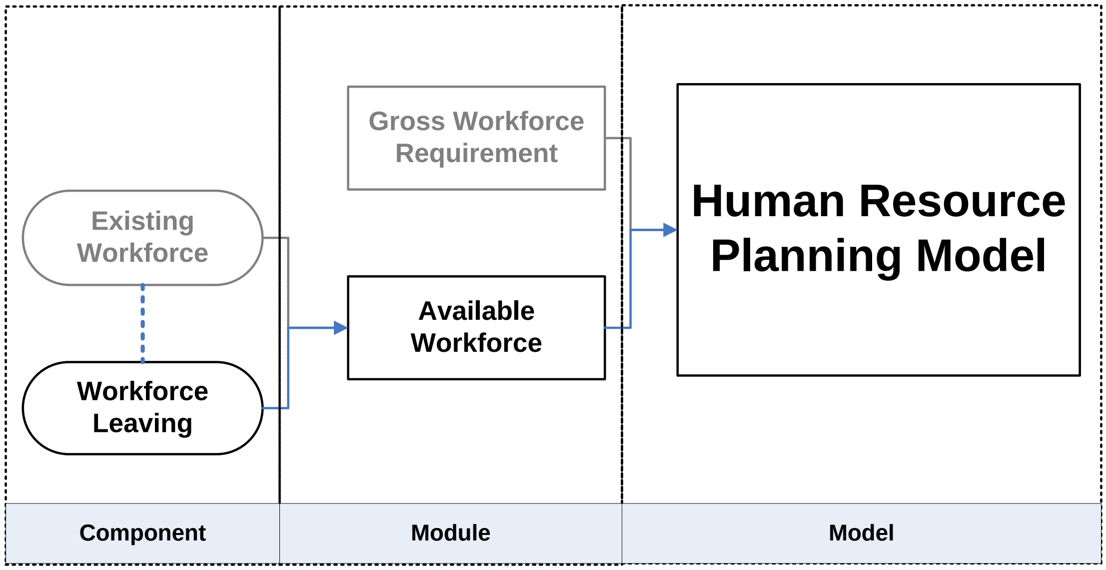


Figure 1: Components and Relationships of the HR planning model

In Figure 1, the highlighted portions are of active interest in this study. As mentioned earlier, the "D" data is given. This approach, when applied to an organization's human resource planning, is expected to encourage awareness of the workforce dynamic, allowing a human resource team to understand their workforce's current and future status and situation.

1.4 General Approach

This HRPM was developed in two major phases, as shown in Figure 2. The first phase consisted of three activities:

- A literature search on human resource planning models;
- The development of an HRPM;

- The identification of the critical information, required to form a systematical planning approach.

In the second phase, a mathematical prediction model was developed. This phase consisted of four steps:

- In the first step, the data was received from the organization and organized to be fed into the model;
- In the second step, the significant predictors were identified based on the least MPAE (Mean Percentage Absolute Error);
- In the third step, regression was performed to develop a staffing equation;
- As the final step, the results were justified and validated by testing the model on holdout data.[1]

[1] The last few data points, removed from a given data series, are called "holdout" data. The remaining historical data series is called "in-sample" data; the holdout data is also called "out-of-sample" data.

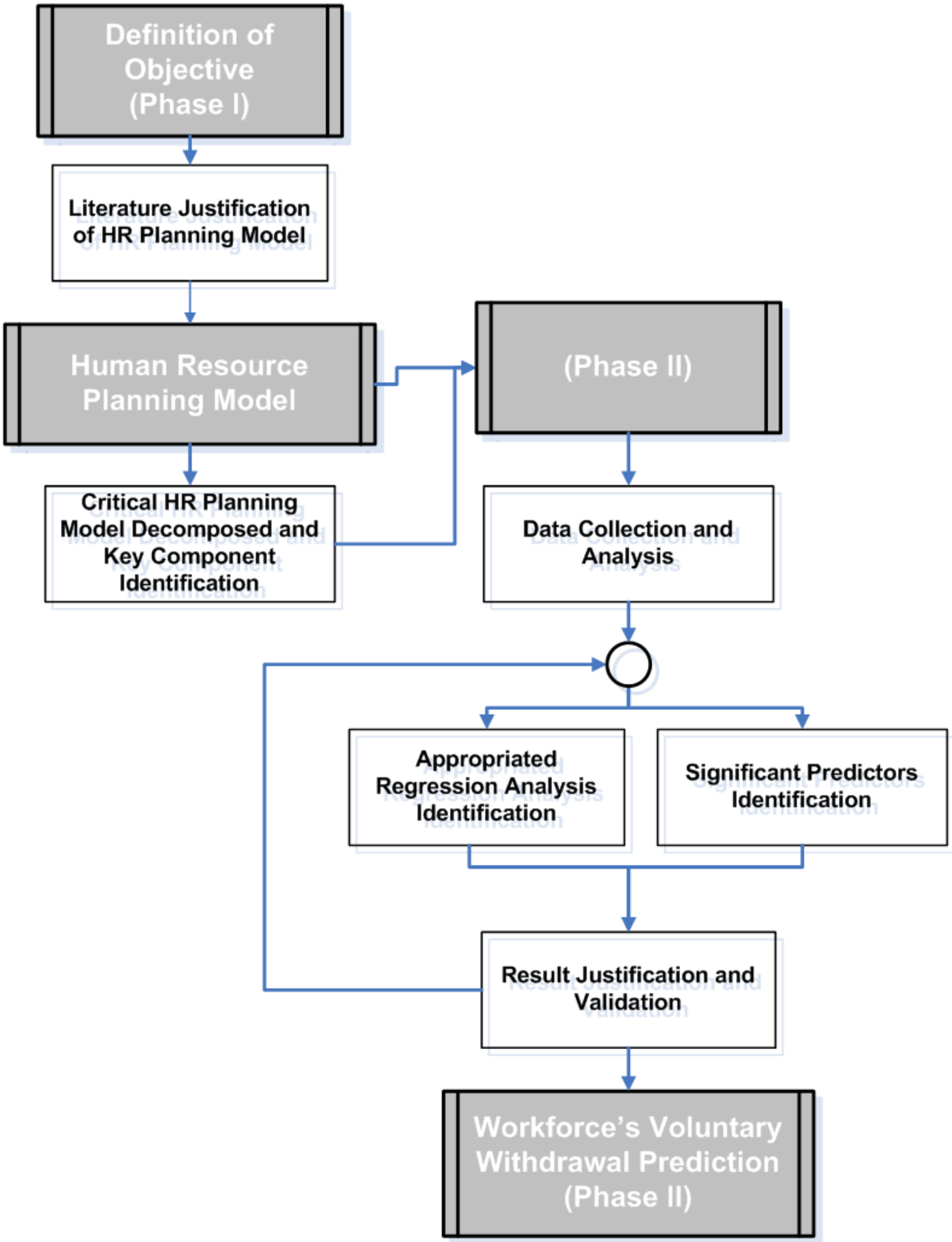


Figure 2: General Approach

1.5 Organization of Thesis

This thesis is presented in five chapters. A brief description of each chapter is presented below;

- Chapter I consists of the introduction, the problem statement, the conceptual framework, the general approach, and the organization of the thesis;
- Chapter II includes a literature review of existing human resource planning and the elements of prediction. It also includes a study of predictors for employee withdrawal;
- Chapter III describes the methodology used to identify significant predictors and to perform the regression analysis;
- Chapter IV presents the implementation of the planning model; and
- Chapter V contains the conclusions and indications for future work.

CHAPTER II

LITERATURE REVIEW

This chapter provides the results of a literature search focusing on two groups of workforce studies. The first group of studies concentrates on approaches related to workforce alignments and workforce planning strategies. The second group of studies focuses on studies related to techniques for the prediction of personnel withdrawal behavior and variables associated with it; these techniques are used to enhance the reliability of planning.

2.1 Human Resource Planning

Workforce planning is designed to ensure that an organization prepares for its present and future workforce needs by having “the right people in the right places at the right time” (Jacobson, 2010). Human Resources (HR) refers to individuals who make up the workforce of an organization (Kelly, 2001). The human resource department in an organization is generally charged with implementing strategies and policies relating to workforce management. Successful human resource planning plays a crucial role in the reinforcement of business strategy performance (F. H. Lee, Lee, & Wu, 2010). The competitiveness of organizations relies on having the appropriate number of employees in order to enhance the organization’s capabilities and efficiency

(Lopez-Cabrales, Valle, & Herrero, 2006). Although the human resource team is a critical player in developing and supporting the human resource planning structure in organizations, the ownership of the plan belongs to top administrators and managers (Keel, 2006). Over the years, many techniques, models and methods have been used to identify appropriate workforce requirements. Table 1 shows a brief summary of the literature review and describes the main human resource planning methodologies, followed by the details of each work reviewed.

Table 1: Summary of Literature Review on Human Resource Planning

Author(s)	Methods	Year
Kwak and Lee	Linear goal programming	1997
Hendriks et al.	Rough-cut project and portfolio planning	1999
Kwak	Fuzzy set approach	2003
Jacobson	Comparison of several different structures of important workforce planning models in the past.	2010
Größler and Zock	System dynamic model	2010
Barber and Lopez-Valcarcel	Simulation	2010

- Kwak and Lee (1997) introduced the technique of linear goal programming in a micro-management program (S. M. Lee & Shim, 1986) for workforce scheduling in health care, with the goal of assigning personnel to proper shift hours. The constraints of the model were constructed based on working procedure regulations such as physician-nurse ratios in order to minimize total payroll costs and maximize manpower utilization.

- Hendriks et al. (1999) proposed five elements to set up an adequate resource-allocation process by using a rough-cut project and portfolio planning method (Platje, Seidel, & Wadman, 1994). They divided the planning into three stages or elements: “long term” (5-year planning), “medium term” (±1-year planning) and “short term” (±5-week planning). Each stage served different purposes and was connected by two elements: the “link” and the “response.” The output of one stage served as the input of the other stages. The “response” stage monitors and evaluates the “link” between two stages. This feedback improved overall planning by adjusting the result over time.
- Kwak (2003) found that goal programming could not handle the organizational differentiation problems generated by a single resource serving multiple requirements. He proposed a fuzzy set approach to generate a simultaneous solution of the complex system in order to deal with uncertain situations.
- Jacobson (2010) evaluated several different structures for workforce planning models. He found similar basic aspects in the models and identified the steps needed to develop a workforce plan. The following are the four fundamental steps proposed:
    - Review organizational objectives

    - Analyze present and future workforce needs to identify gaps or surpluses
        - In the analysis, the current workforce needs are determined based on demographics, retirement eligibility statistics, employee skills/competencies, salary data, the correlation between employee turnover and skill set availability, etc.
        - The most significant factors affecting the future workforce needs are the factors affecting demand for services, critical positions, required skill sets, predicted change in the workforce, impact of legislative changes, and socio-economic changes, among others.
        - Finally, the gap analysis was done based on the difference between projected need and projected supply.
    - Develop and implement human-resource strategies and plan
    - Evaluate, monitor and adjust the plan.
- Größler and Zock (2010) introduced the system dynamic model, which utilizes a modeling and simulation method to reduce lead time in the overall recruiting process. This approach was originally utilized to enhance supply-chain performance, but it was applied in this case to personnel-supply problems. In this case, it helped the researchers gain insight into the problem and to reduce the variations in the recruitment and training processes

- Barber and Lopez-Valcarcel (2010) used a simulation technique to analyze the results of diverse human-resource policies of the health-care system in Spain. Because the people involved in health require many years to gain professional experience, the model also considered demographic, education and labor-market variables as dynamic factors.

2.2 Employee Withdrawal and Variables

Employee attrition and methods for predicting voluntary withdrawal have been examined by several researchers. The prediction of employees' withdrawal gives HRPM the critical information to produce practical results. The following presents some research efforts on workforce prediction:

- Markov Analysis (MA) is one of the prediction tools utilized to study internal workforce movement throughout an organization, as well as exit occurrences (Heneman & Sandver, 1977). Fundamentally, MA translates the organizational structure into mutual states based upon function and hierarchy. These states are then arranged into a matrix, with the current state occupying rows and the immediate successor states, as well as the exit option, occupying the columns. Assuming the conditions of constancy in the organization and the external environment, this transition matrix, developed from historical data, demonstrates the probability of a worker's transition from one job level to another. MA has been used to describe the internal labor markets by organizations, to audit labor practices, to do career planning and development, to forecast internal labor supply for the future and to engage in affirmative-action programs.

- Mobley et al. (1979) reviewed several studies attempting to find a relationship between potential variables and turnover behavior. This study was generic in nature, not industry-specific. The following list summarizes the crucial independent variables at the individual level:
    - Personal factors
        - Age: The age of an employee is the most significant independent variable of turnover rate. It has negative response to turnover rate. That is, older workers are less likely to leave their jobs, so turnover decreases with age (Federico, Federico, & Lundquist, 1976; Marsh & Mannari, 1977; Mobley, et al., 1979).
        - Education: The role of the education level of an employee is still unclear. Independent studies disagree on how education affects turnover rate (Federico, et al., 1976; Hellriegel & White, 1973).
    - Job satisfaction: At least two studies indicate a negative relationship between overall job fulfillment and turnover. That is, an employee who feels unfulfilled at a job is more likely to leave it (Marsh & Mannari, 1977; Mobley, et al., 1979).

    - Salary expectation: Federico (1976) found that higher pay was connected to longer tenure. However, even those who were paid more were likely to leave if they were not satisfied with their pay.
    - Economic conditions
        - Unemployment: Woodward (1975) found a negative relationship between the unemployment rate and turnover. People are less likely to leave their jobs when unemployment is higher.
        - Unfilled Vacancies: Woodward (1975) also found a positive correlation between available job vacancies and turnover rate. That is, when other jobs are more available, employees are more likely to leave.
- Michaels and Spector (1982) performed a test on Mobley, Griffeth, Hand, and Meglino's turnover model in four different case studies, raising a question about the direct effect of labor-market conditions on turnover. They found that organizational commitment was excluded from the model. This result was confirmed by Marsh and Mannari's research (1977). The latter found that Japanese companies' turnover is lower than US companies' turnover precisely because of the organizational commitment.
- Muchinsky and Tuttle (1979) reviewed several studies on the basis of common variables for turnover prediction. The job profiles taken into

consideration had a wide variety. It included telephone operators, service representative, foremen, sales managers, engineers, psychiatric aides, life insurance salesmen among many other categories. The predicting variables were separated into the following five groups:

  - Job Attitude
  - Biological Data
  - Work-Related Data
  - Personal Data
  - Test Scores

  They concluded that the results of the many empirical turnover studies were controversial.

- Taylor and Shore (1995) conducted a survey distributed to 264 respondents of an unnamed multinational corporation in order to research the significant factors and predictors of planned retirement. The result indicated that employees with low retirement benefit levels delayed retirement. Retirement-eligible employees extended their years of service if they were not satisfied with their retirement benefits. This survey also revealed that self-rated health was the strongest predictor of planned retirement.
- Somers (1999) found a nonlinear relationship between employees' withdrawal behavior and employee attrition with respect to the correct

classification of employees who left employment (“leavers”). This study was conducted on a sample group of 577 hospital employees.

The conventional methods did not provide a comprehensive prediction model considering real world variables of market conditions as well as personality traits. They simply pointed out certain relevant indicators that effect turnover. Somers is closest to a prediction model using statistical tools. He however considered only personality traits, which completely ignored the business environment and as such will not be effective in prediction.

This Thesis attempts to build a comprehensive employee turnover prediction model using a logistic regression model and involving personality as well as economic data. The marriages of these aspects have never been experimented before. The use of the ‘interaction variable’ further fine tunes accuracy.

CHAPTER III

MATERIALS AND METHODS

The review of relevant literature in Chapter II highlighted some deficits in the methods and techniques used for human-resource planning. This brought about the conclusion that the conventional methods did not provide a comprehensive prediction model considering real world variables of market conditions as well as personality traits. Therefore how can an organization predict employee turnover so as to balance organizational goals, budgets, employee morale, and overheads over the long term? This chapter focuses on the methodology for addressing those drawbacks and presents a forecasting model for voluntary employee withdrawal in an organization. The method requires an in-depth understanding of the specific relationship between employees' withdrawal behavior and the factors that affect the behavior. The model utilized in the human resource-planning process is expected to adequately predict workforce needs to allow employers to maintain the required staffing levels. The coefficients for the model are developed based on the original set of data. However this model assumes environmental variables in the analysis and hence the model is flexible in incorporating the environmental factors in addition to personnel data. The next section demonstrates the conceptual framework of human-resource planning and is adapted from the approach used for materials requirements planning.

3.1 General Approach of Human-Resource Planning

In dynamic business environments, organizations have to plan to achieve the optimal staffing levels that will be required over predetermined time periods. Since the workforce is not always aligned with the requirements of the organization at a given time, adjusting the workforce in turn increases an organization's budgetary expenditures. The main objective of this model is to align the workforce with the organization's requirements, not only helping the human-resource team minimize overall operating cost, but also making sure that the organization always has ample staffing to serve its needs.

Materials Requirements Planning (MRP) has been known for a very long time as a tool for managing and minimizing the physical flow of inventory. MRP generally consists of two major modules, demand and supply; these are linked to each other by a master schedule, which helps manage demand and supply to serve sales (Hopp & Spearman, 2007). The ideal of MRP is to have the right amount of inventory to produce or purchase exactly what the customer wants (van der Laan & Salomon, 1997). In order to minimize the total cost, several of factors have to be considered such as shelf life, holding cost and/or ordering cost etc (Whitin, 1955).

MRP activity is similar in concept to workforce management in aligning workforce level and workforce demand. In fact, the fundamental principle of HRPM (Human-Resource Predictive Model) is based on MRP (Material Requirement Planning). As a result, the general human resource planning approach has been formed. As mentioned in Section1.3, this study anticipates that a given organization has the ability to forecast the value of D, the future workforce demand.[2] Figure 3 demonstrates the relationship between current available workforce and future workforce demand (D) which can be illustrated by clearly understanding the relationship between:

- T (time horizon of prediction)
- D (number of employees needed).
- OH (on-hand workforce),
- VW (voluntary withdrawal)
- R (changing required in workforce level).

[2] In this study we do not anticipate any changes in process. However if a change in process and the organization can anticipate and predict the corresponding D, the model still holds true and w ill remain valid.

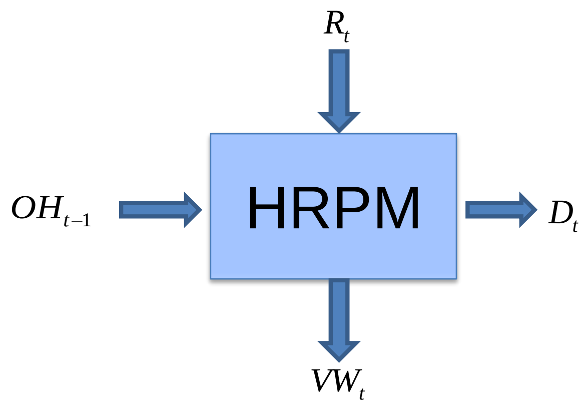


Figure 3: Human resource Planning General Approach

As an illustration, the approach was transferred to the human resource planning equation, as shown in Equation (1)

$$R_t = D_t - [OH_{t-1} - VW_t] \quad (1)$$

The value of R can be interpreted as follows:

- Positive number: additional workforce is needed
- Negative number: a reduction in workforce is necessary
- Zero: the workforce is perfectly balanced.

In order to account for human exigencies, it is assumed that the input D value contains corresponding tolerances. The numerical value of $R_{t.}$ is not an absolute, in terms of the HR Manager's decision. It is a scientific reference point for decision making.

The process of evaluating employee withdrawal will be demonstrated in detail in the following section.

3.2 Prediction of Voluntary Workforce Withdrawal

This prediction considers only voluntary withdrawal. Other types of withdrawal such as discharges, lay-offs, and deaths will not be considered in this particular model. Discharges and lay-offs are organizational decisions. Death is an event which is beyond control. This goal of this model is to predict voluntary withdrawal of employees and the above mentioned reasons are not within the employee's voluntary decision making. Hence the model holds true even without consideration of these factors. The procedure for determining the workforce voluntary withdrawal prediction by means of regression analysis consists of six stages. The first stage involves data gathering, followed by stage two, decomposition of the data characteristics based on a self-selection model. In stage three, critical predictors are identified, and in stage four, regression analysis is performed on all relevant predictors. The fifth stage includes model validation, and the final stage is the implementation.

Stage 1: Data Gathering

- The time horizon of the prediction is identified (i.e., over what period of time is the prediction desired?)

- Data is gathered from authorized personnel with detailed information about the workforce of the organization, as shown in Table 2. These data includes basic information such as employee names, ages, job titles, and salaries. The response ‘y’ is a measure of predictive data for the future which is shown in the third column; ‘0’ indicates that the employee was in the service at a given time as shown in the second column, and ‘1’ indicates that the employee was not in service at the given time also shown in the second column.

Table 2: Sample of the data-gathering worksheet

Employee’s ID	Time Horizon	y (in service)	Info 1	Info 2	Info 3	Info n
1001	1					
1001	2					
1001	3					
1001	t					
1002	1					
1002	2					
1002	3					
1002	t					
1000+u	1					
1000+u	2					
1000+u	3					
1000+u	t					

- Reserve some sample data from the original database to use for validation in the later steps.
- Modify and refine the data to a user-friendly form as the original data may not necessarily be user-friendly. In such cases, the data need to be modified and refined to yield a “cleaner,” form as shown in Table 2.

Stage 2: Decomposition of Workforce Characteristics

The master dataset is analyzed for the levers that have the most impact on turnover. It could be location, retirement benefits, workplace culture etc. On such basis, the dataset is separated. The process of separation of the workforce dataset follows a ‘self-selection’ or ‘sample selection’ model by adding a decision equation, as shown in Equation (2). The decision equation decomposes observations on individuals who were self-selected into the sample on the basis of a criterion that is correlated with the dependent variable of the outcome equation (Heckman, 1979).

$$y = \begin{cases} X^T\gamma + \delta \ \ if \ I^* = 1 \\ X^T\beta + \varepsilon \ \ if \ I^* = 0 \end{cases} \qquad (2)$$

In workforce withdrawal prediction, there are several factors that can be used in the decision equation as explained in the preceding paragraph. One of the most possible decision equations is based on retirement eligibility because of retirement benefits. Retirement eligibilities are highly organization-specific.

People who have left an organization to retire when they were eligible have a full right to get a pension provided by the organization, insurance company, and/or government. Consequently, being retirement-eligible could be used as a decision equation indicating the motivational factors for an employee's withdrawal.

Stage 3: Critical Predictor Identification

The prediction model's accuracy relies on a set of combinations of independent variables consisting of the following groups:

- Direct factors
- Indirect factors
- Interaction factors
- The time period indicator matrix.

The time horizon matrix variables are additional variables eliminating the seasonal characteristics of the data. In this study dataset, employees tended to quit the job during some particular period of the year. This variable allows the model to control the change of withdrawal related to recurring events. For example, if the period of three months (quarterly) is set to be the time horizon, the matrix will be determined as follows:

- [0 0 1] refers to Q1
- [0 1 0] refers to Q2
- [1 0 0] refers to Q3

- [0 0 0] refers to Q4

A number of studies have been conducted seeking the relevant factors or significant predictors of employee withdrawal, as mentioned in Chapter II. However, the combinations of significant variables in different datasets vary depending on an organization's culture. An initial set of predictors can be gathered from a group of people who know the nature of the organization, and then irrelevant factors can be eliminated to refine the group of significant variables by using Akaike Information Criterion (AIC) (Bozdogan, 1987), as shown in Equation (3). 'AIC' is a measure of the relative goodness of fit of a statistical model. It offers a relative measure of the information lost when a given model is used to describe reality and as such is describes the tradeoff between 'bias' and 'variance' in the model construction. AIC is a relative selection tool with no standard optimal AIC value and it selects the best model among all alternatives. The combination of predictors that gives the minimal value of AIC is selected.

$$AIC = 2k - 2\ln{(L)} \tag{3}$$

where

- k is the number of parameters in the model
- L is the likelihood function for the model.

Table 3 shows a sample of the critical predictor identification worksheet. The highlighted sections are examples of predictors indicating statistically insignificant to decision equations. In the sample worksheet, predictor 1, for example, is relevant to exclusively $I^* = 1$.

Table 3: Critical Predictor Identification Worksheet

Decision Equation	Predictor 1	Predictor 2	Predictor 3	Predictor 4	Predictor n
$I^* = 1$					
$I^* = 0$					

Stage 4: Regression Analysis

Initially Linear Regression was employed to predict the workforce withdrawal number. However this method was not successful as the actual data was far from linear as shown in Figure 4 and Figure 5.

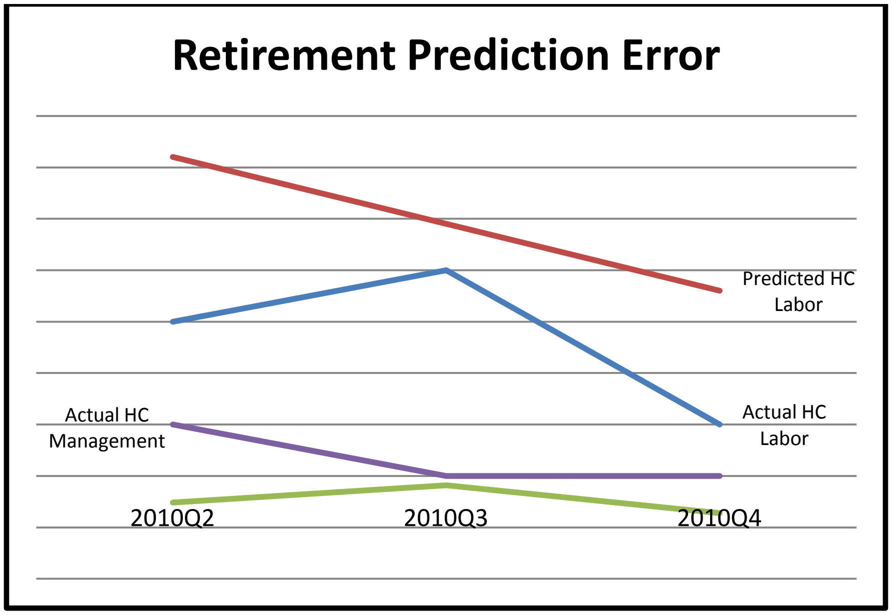


Figure 4: Incompatibility of Predicted Data from Linear Regression and Actual Data in Retirement Eligible Employee

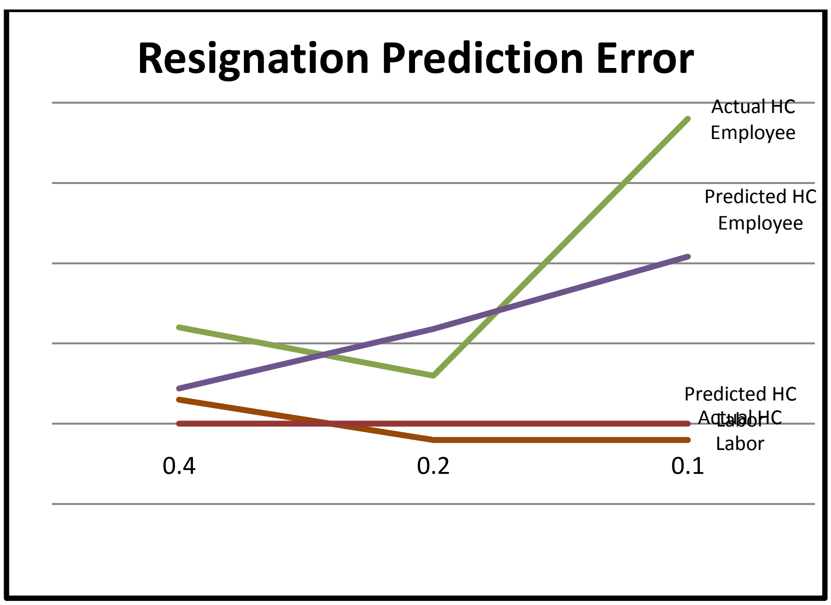


Figure 5: Incompatibility of Predicted Data from Linear Regression and Actual Data in Retirement Ineligible Employee

Workforce withdrawal was analyzed to have binary outcomes and this leads us to binary regression modeling. This paper will introduce logistic binary regression modeling to find the probability of individual volunteer withdrawals (dependent variables, shown by Y) given by a set of relevant predictors (independent variables, shown by X) consisting of direct factors, indirect factors, the time period indicator matrix, and interaction factors

In binary regression theory, the dependent variable is equal to 1 when the event occurs and 0 when the event does not occur (Durlauf & Blume, 2010). This is known as a dummy output variable. In workforce planning, the occurring event (Y = 1) refers to the individual's leaving and the non-occurring event (Y = 0) refers to the individual continuing working in service. Therefore, logistic regression is utilized to seek the probability of the event occurring given by independent variables.

The logistic regression model determines an equation that calculates the probability of event Y occurring to maximize the likelihood function. The model is formed by parameterizing the probability *p* depending on repressor vector X and parameter vector β. The model is an identical conditional probability given by Equation (4):

$$p_i \equiv Pr[Y_i = 1/X] = F(X_i'\beta) \tag{4}$$

Equation (5) presents the most common form of logistic binary regression model:

$$p = \wedge (X'\beta) = \frac{e^{X'\beta}}{1 - e^{X'\beta}} \quad (5)$$

The logistic maximum likelihood (MLE) first-order conditions is simplified into the following, Equation (6)

$$\sum_{i=1}^{N} \big(Y_i - \wedge (X_i'\beta)\big) X_i' = 0 \quad (6)$$

This simple form is similar to the ordinary-least-squares (OLS) regression and it arises because it demonstrates the canonical link function for the Bernoulli density.

The regression coefficients that have been calculated by using logistic regression analysis are shown in Table 4

Table 4: Regression Coefficients Worksheet

Decision Equation	Predictor 1	Predictor 2	Predictor 3	Predictor 4	Predictor n
$I^* = 1$	γ_1	γ_2	0	γ_3	γ_n
$I^* = 0$	0	β_2	β_3	β_4	β_2

Stage 5: Final Workforce Requirements and Recommendations

In this phase, The probability of employee withdrawal (*p*) is calculated from Equation (5) using the regression coefficients as shown in Table 4 and employee's information as shown in Table 2. Then HC' is estimated from equation below.

$$HC' = OH_{t-1} - (\bar{p} * Workforce\ Size) \tag{7}$$

Table 5 shows the recommendations that should be done to serve the demand number.

Table 5: Sample of the Final Results and Recommendations

Time Horizon	Demand	Total HC'	Requirement	Cumulative Requirement
t+1				
t+2				
t+n				

Where

- Demand = workforce gross requirement

- Total HC' = the grand summation of the predicted HC' in every decision equations
- Requirement is calculated based on Equation (8).

$$\mathrm{Requirement}_{t+n} = \mathrm{Demand}_{t+n} - (\mathrm{Total\ HC'}_{t+n-1} + \mathrm{Cum.Req}_{t+n-1}) \qquad (8)$$

Stage 6: Implementation

The last stage of the model involves developing a user-friendly interface of the human-resource planning model in Microsoft Excel Macro. The user simply has to upload the input data into an inbuilt excel file. The software will process the data to give the output. This eliminates any need for manual computations and gives a definitive output.

The program performs human-resource planning based on determined predictor coefficients with a dynamic dataset. It will transfer and utilize the initial information from “RAW.xlsx” to arrive at a suggestion for workforce alterations. Sample source code for the program is shown in Appendix 2.

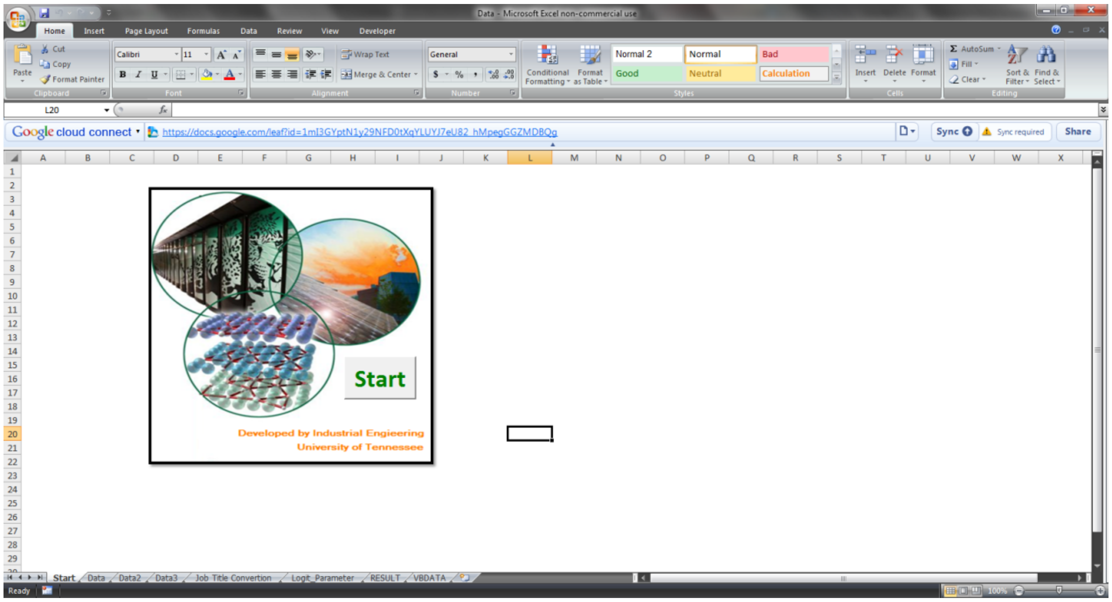


Figure 6: Screen Shot of Start Page

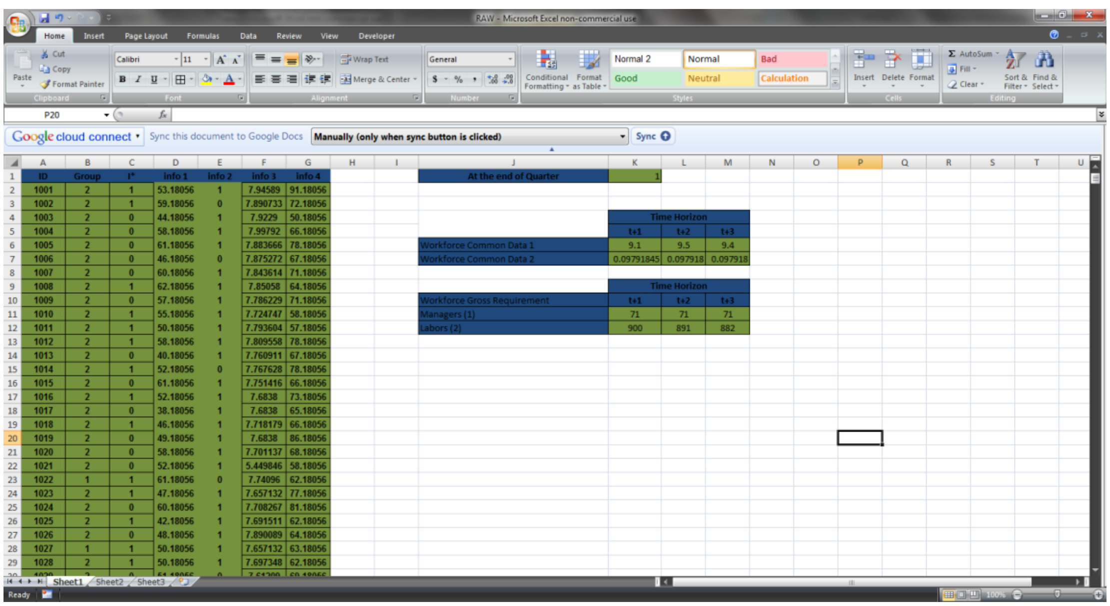
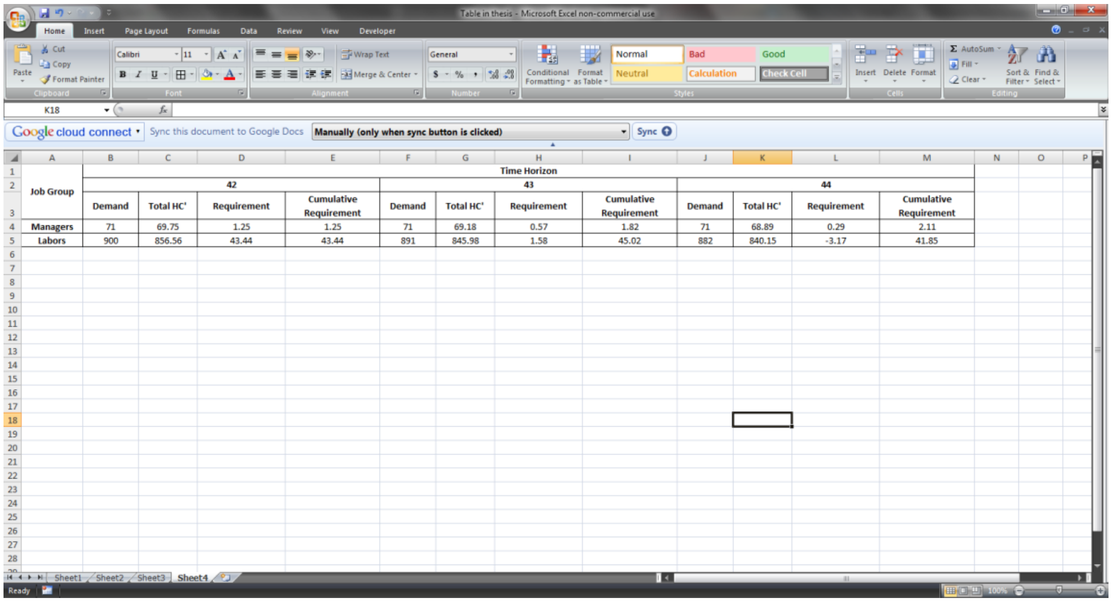


Figure 7: Screen Shot of RAW.xlsx



Job Group	Time Horizon											
	42				43				44			
	Demand	Total HC'	Requirement	Cumulative Requirement	Demand	Total HC'	Requirement	Cumulative Requirement	Demand	Total HC'	Requirement	Cumulative Requirement
Managers	71	69.75	1.25	1.25	71	69.18	0.57	1.82	71	68.89	0.29	2.11
Labors	900	856.56	43.44	43.44	891	845.98	1.58	45.02	882	840.15	-3.17	41.85

Figure 8: Screen Shot of Result Worksheet

CHAPTER IV

RESULTS AND DISCUSSION

Chapter IV illustrates a workforce withdrawal prediction for a human-resource planning model using historical data obtained from a government agency. The case study was drawn from 11 years' worth of records of the organization's employment data. This organization had datasets for two groups:

- Managers
  - In this study, the working definition of a manager is that of a person who occupies one of the four manager level grades as classified by the HR policy of the organization. The four grades are namely M1, M2, M3 and M4, M4 in the ascending order of grade. A total of 71 managers in a certain division were considered here.
- Craftsmen
  - For the purposes of this study, the working definition of a Craftsman is that of a person who occupies one of the ten 'L' level positions as classified by the HR policy of the organization. The ten grades are L1 through L10 in the ascending order of the base salary. At the time of the study there were 894 personnel who belonged to this category and participated in the study.

Step 1: Data Gathering

The horizontal time of the model was defined as the quarter. There were datasets on two groups (managers and Craftsmen). In the organization, each dataset covered 41 consecutive quarters. Quarters ‘1–38’ were used for the prediction and quarters ‘39–41’ were used as ‘holdout data’ for the validation process. The initial dataset contained information on

- Employee ID
- Job Title
- Date of Hire
- Date of Termination
- Division of organization
- Race
- Gender
- Number of Employee Points
- Years of service (YCS)
- Age
- Base Salary

Step 2: Decomposition of Workforce Characteristics

In this case study, the data were decomposed into two groups: retirement and resignation. Retirement is defined as voluntary withdrawal from a job in a manner that satisfies the organization’s retirement criteria. Voluntary retirees get associated benefits or pensions depending on their individual retirement plan. The pension plan will be established by the organization. Retirement-eligible employees tend to consider the pension benefit as one of the withdraw decision factors. Resignation is also a form of voluntary withdrawal but does not fully satisfy the organization's retirement criteria. Resignation is a withdrawal that does not accord pension rights, whereas, retirement entails a continuing relationship with the organization with pension benefits. Consequently, the withdrawal behavior may be different. Therefore, the decision equation was followed by the proposition as shown in Equation (9). In this case study, there were two criteria for receiving retirement benefits, of which an employee had to meet at least one to be considered as retirement eligible. An employee meeting retirement eligibility has the choice to continue working or to opt for voluntary retirement. The following are the criteria for voluntary retirement;

- Age: employee is 65 years old or over
- Point: employee has more than 85 points (point is the sum of the employee's age and the total working year of the employee in this organization)

$$y = \begin{cases} X^T\gamma + \delta \text{ if (age} \geq 65 \text{ or point} \geq 85) \\ X^T\beta + \varepsilon \text{ if (age} < 65 \; \textit{and point} < 85) \end{cases} \tag{9}$$

Step 3: Critical Predictors Identification

After analysis on withdrawal variables, the initial set of predicting variables have been iterated down to the following.

- Employee information
  - Gender
  - Number of Employee Points
  - Years of service (YCS)
  - Age
  - Base Salary
- Economy condition
  - Percentage change from *NYSE: NYA*[3] $_{t-1}$ to *NYSE: NYA* $_t$
    - The readings of the NYSE: NYA is taken for 2 two timestamps. The primary reading is the average index value of a given quarter and the secondary reading is the same, from the previous quarter. The percentage change between these readings is calculated and this number is taken as one of the input variables.
  - Unemployment Rate (UR)
    - The unemployment rate is a measure of the prevalence of unemployment and it is calculated as a percentage by dividing the number of unemployed individuals by all individuals currently in the labor force.

---

[3] New York Stock Exchange Composite Index

- Time period indicator: Analysis showed that attrition rates varied according to the quarter of a given fiscal year. In order to accurately capture these seasonal variations, four independent variables were generated, namely q1, q2, q3 and q4, where q1 denotes quarter1 of the fiscal year, q2 the second quarter of the fiscal year and so forth. All the quarters of the master dataset are mapped to these variables in a matrix. This is illustrated in Table 6.

Table 6: Example of Time Period Indication

Time Horizon	q1	q2	q3	q4
1	1	0	0	0
2	0	1	0	0
3	0	0	1	0
4	0	0	0	1
5	1	0	0	0

However, after a preliminary analysis of the historical data, it was determined that the initial variables were not adequate to predict the likelihood of an employee’s voluntary withdrawal. Therefore, an analysis of the interactions between variables was required. Figure 9 populates the employee withdrawal according to age and YCS. As a result, the following variable was developed:

- Interaction between variables: the shape of Figure 9 is exponential function from low age low YCS to high age high YCS. Therefore the variable “LN (Age x YCS)” is formulated (note: log function is to level the value of Age x YCS).

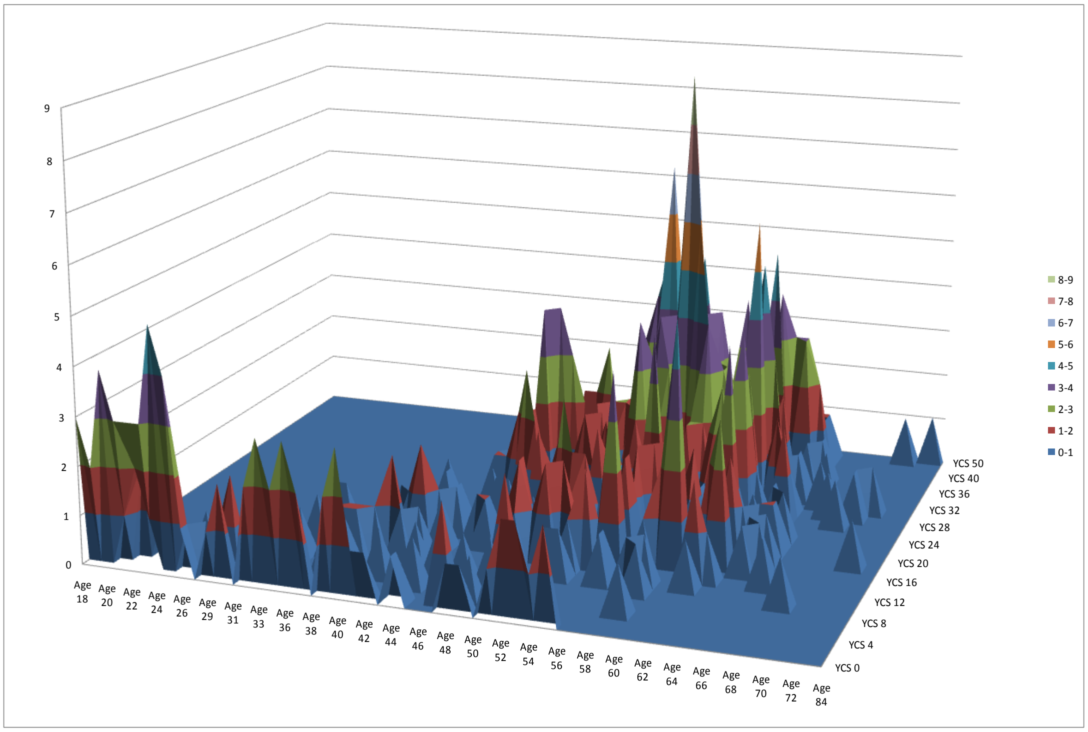


Figure 9: Interaction between YCS and Age

- Age range: these variables (grp1, grp2, grp3) were used to indicate the age ranges to which employees belonged. In order to locate the knots or separating points of this discrete data, the slope of Figure 10 was analyzed. The changing points of the slope were identified as the knot ‘41’ and knot ‘56’. The ages of 41 and 56 are transition points in the data set, where the populations of the employees show a sharp increase after the age of 41 up to 56. Research has established that this is primarily because at around the age of 40, people think of a job shift considering long term career advancement. After 56 there is a sharp decline in the employee population. Again, research shows that during the mid-fifties people tend to stay on in their current organization as they near retirement.

- Further the values of each group were represented numerically as ‘0’ or ‘1’. The three ranges were the following:
    - “grp1” = 1 if the individual employee was less than 41 years old.
    - “grp2” = 1 if the individual employee was between 41 and 56 years old.
    - “grp3” = 1 if the individual employee was more than 56 years old.

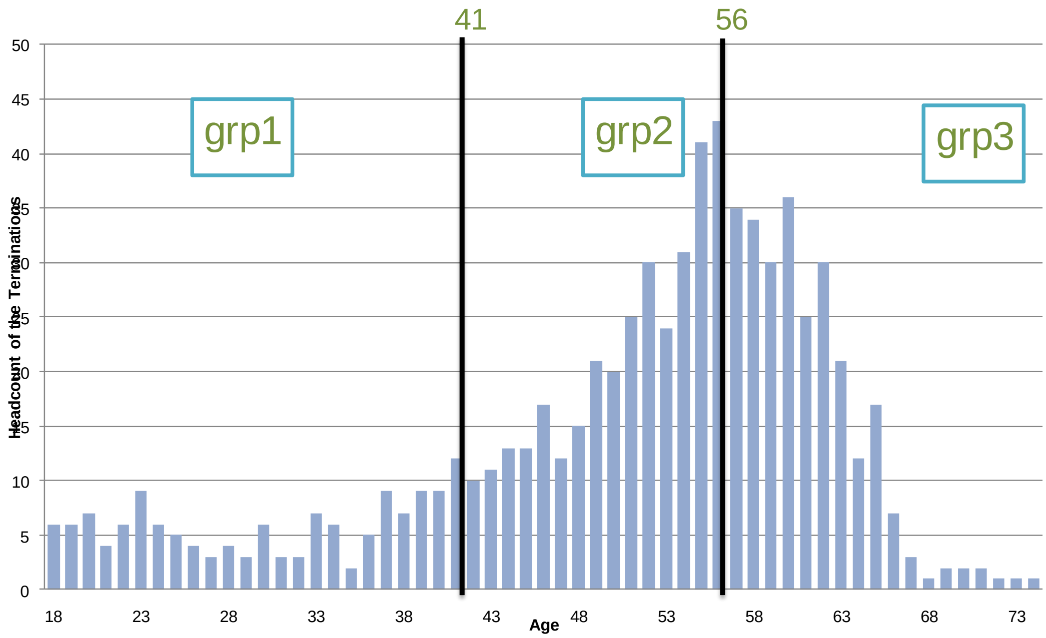


Figure 10: Demographic Decomposition by Employee's Age

There are 511 possible combinations of the nine variables. The combination for which the AIC value is least is chosen. Table 8 shows the final result of the variable combination selection. The final combination was also tested by comparing predicted employee withdrawal and actual employee withdrawal during the holdout quarters 38-41 by computing the MAPE (Mean Absolute Percentage Error) values as shown in Table 7.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - P_t}{A_t}\right|$$

Where

- A is the actual value

- P is predicted value
- n is the number of fitted points

Table 7: Result Verification

Time Horizon		38	39	40	41	MAPE
Job Group	**Job Title**	**%Error**	**%Error**	**%Error**	**%Error**	
Manager	M1	4.57%	2.50%	-0.58%	-6.92%	0.04
	M2	-1.56%	-0.47%	-0.29%	-5.17%	0.02
	M3	-0.73%	-0.23%	-0.14%	26.98%	0.07
	M4	-0.10%	-0.08%	-0.05%	-0.14%	0.00
Craftsman	L1	-1.59%	1.15%	-0.12%	-0.33%	0.01
	L2	-1.07%	-0.75%	-0.66%	-1.42%	0.01
	L3	-0.96%	5.04%	-0.62%	-1.60%	0.02
	L4	-1.37%	-1.55%	-0.98%	-2.95%	0.02
	L5	-1.09%	-1.27%	-0.78%	-2.57%	0.01
	L6	2.41%	2.55%	1.07%	-2.09%	0.02
	L7	-0.69%	-0.54%	-0.44%	5.60%	0.02
	L8	0.22%	2.26%	-0.71%	-0.48%	0.01
	L9	-0.35%	-0.36%	-0.13%	-0.78%	0.00
	L10	0.92%	-0.03%	0.28%	3.57%	0.01

Table 8: Final Combinations of Predictors

Group		Notation	Managers		Craftsmen	
Retirement			Eligible	Ineligible	Eligible	Ineligible
Variables	Gender	X1	√	√	√	√
	Retirement Point	X2		√		
	Year of Service (YCS)	X3				
	Age	X4		√		√
	Salary Ranking	X5	√	√	√	√
	Age Range Matrix	X61-X63	√		√	
	Quarter Matrix	X7	√	√	√	√
	Delta(NYSE)	X8	√	√	√	√
	Unemployment Rate	X9	√	√	√	
	ln (Age*YCS)	X10	√		√	

Note: √ indicates the significance of the variable

Step 4: Regression Analysis

In this step, the statistical software, Stata10, was utilized to calculate the coefficients of the employee withdrawal variables. The table in Appendix 1 provides a detailed illustration of the variable coefficients of four groups to formulate logistic regression model as shown in Table 9.

Table 9: Logistic Regression Predictive Model

Group	Logistic Regression Equations
Manager (Retirement Eligibility)	$\hat{y} = \frac{e^{((-0.31543 \bullet X1)+(-0.09976 \bullet X5)+(-0.4315918 \bullet X61)+(-0.7901729 \bullet X62)+(0.210748 \bullet X7)+(-0.040476 \bullet X8)+(0.2039285 \bullet X9)-3.9628)}}{1-e^{((-0.31543 \bullet X1)+(-0.09976 \bullet X5)+(-0.4315918 \bullet X61)+(-0.7901729 \bullet X62)+(0.210748 \bullet X7)+(-0.040476 \bullet X8)+(0.2039285 \bullet X9)-3.9628)}}$
Manager (Retirement Ineligibility)	$\hat{y} = \frac{e^{((0.764158 \bullet X1)+(-0.0170573 \bullet X2)+(0.095276 \bullet X4)+(-0.06896 \bullet X5)+(-0.4315918 \bullet X61)+(-0.7901729 \bullet X62)+(0.210748 \bullet X7)+(-0.040476 \bullet X8)+(0.2039285 \bullet X9)-3.9628)}}{1-e^{((-0.31543 \bullet X1)+(-0.09976 \bullet X5)+(-0.4315918 \bullet X61)+(-0.7901729 \bullet X62)+(0.210748 \bullet X7)+(-0.040476 \bullet X8)+(0.2039285 \bullet X9)-3.9628)}}$
Craftsman (Retirement Eligibility)	$\hat{y} = \frac{e^{((-0.31543 \bullet X1)+(-1.050649 \bullet X5)+(8.513285 \bullet X61)+(-1.400589 \bullet X62)+(0.709912 \bullet X7)+7.211495)}}{1-e^{((-0.31543 \bullet X1)+(-1.050649 \bullet X5)+(8.513285 \bullet X61)+(-1.400589 \bullet X62)+(0.709912 \bullet X7)+7.211495)}}$
Craftsman (Retirement Ineligibility)	$\hat{y} = \frac{e^{((1.355721 \bullet X1)+(-0.8972222 \bullet X5)+(-0.67955 \bullet X61)+(-0.81867 \bullet X62)+(2.278822 \bullet X7)+(-0.00696 \bullet X8)+(0.689514 \bullet X9)-0.43939)}}{1-e^{((1.355721 \bullet X1)+(-0.8972222 \bullet X5)+(-0.67955 \bullet X61)+(-0.81867 \bullet X62)+(2.278822 \bullet X7)+(-0.00696 \bullet X8)+(0.689514 \bullet X9)-0.43939)}}$

Stage 5: Recommendations

$\bar{p}$ in Equation (7) was the average of $\hat{y}$ provided in Table 9 depended on job group. HC' of each employee group were calculated by using Equation (7). Then, R_t or 'Requirement' were calculated by using Equation (8) and recorded In Table 10 and Table 11. These recommendations will guide the human resource team as they plan the organization's workforce recruitments. In Table 10 and Table 11, the demand column shows the demand for the given quarter. The Total HC' illustrates the predicted headcount for that quarter. The requirement displays the required manpower to reach the demand for that quarter. The cumulative requirement at any given row depicts the overall headcount needed through that quarter from the initial quarter of the forecasted dataset.

Table 10: HR Approach for Manager Group

Time Horizon	Demand	Total HC'	Requirement	Cumulative Requirement
42	71	69.75	1.25	1.25
43	71	69.18	0.57	1.82
44	71	68.89	0.29	2.11

Table 11: HR Approach for Craftsman Group

Time Horizon	Demand	Total HC'	Requirement	Cumulative Requirement
42	900	856.56	43.44	43.44
43	891	845.98	1.58	45.02
44	882	840.15	-3.17	41.85

Table 12 shows requirement based on job titles. This information gives the human resource team more in-depth information to manage their workforce.

Table 12: HR Approach for 14 Job Titles

Time Horizon		42				43				44			
Job Group	Job Title	Demand	Total HC'	Req.	Cum. Req.	Demand	Total HC'	Req.	Cum. Req.	Demand	Total HC'	Req.	Cum. Req.
Manager	M1	30	26.4	3.6	3.6	30	25.7	0.7	4.3	30	25.4	0.3	4.6
	M2	28	26.3	1.7	1.7	28	25.8	0.5	2.2	28	25.7	0.1	2.3
	M3	12	9.8	2.2	2.2	12	9.7	0.1	2.3	12	9.7	0	2.3
	M4	1	1	0	0	1	1	0	0	1	1	0	0
Craftsman	L1	102	98.8	3.2	3.2	100	97.2	-0.4	2.8	99	95.5	0.7	3.5
	L2	1	1	0	0	1	1	0	0	1	1	0	0
	L3	20	16.7	3.3	3.3	20	16.6	0.1	3.4	20	16.4	0.2	3.6
	L4	34	33	1	1	33	32.6	-0.6	0.4	32	32	-0.4	0
	L5	53	51.6	1.4	1.4	53	51.1	0.5	1.9	52	50.3	-0.2	1.7
	L6	55	53.9	1.1	1.1	53	53.2	-1.3	-0.2	53	52.6	0.6	0.4
	L7	31	29.7	1.3	1.3	30	29.5	-0.8	0.5	30	29.3	0.2	0.7
	L8	83	79.7	3.3	3.3	83	78.9	0.8	4.1	83	77.7	1.2	5.3
	L9	408	399.2	8.8	8.8	405	395.5	0.7	9.5	399	390.9	-1.4	8.1
	L10	113	111.3	1.7	1.7	113	110.4	0.9	2.6	113	109.4	1	3.6

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Research

The main purpose of this research was to develop predictive ability of the human resource requirements for a large complex organization. The initial methodology of linear regression used to predict the expected number of workforce withdrawal showed inaccurate results as the actual data was not linear but binary in nature.

To get effective predictions of binary data, the ‘logistic regression model’, a non-linear regression model, was chosen. The new prediction results arrived at, using this model showed very good accuracy with minimal deviation from the actual data. On testing the model on the holdout data, the results showed high accuracy levels with MAPE measurements well below 5%. (As a standard, readings below 10% MAPE are considered good predictions with high acceptability).

The Demand ‘D’ for a particular period is given by the organization which is input into the model. The model computes the Requirement, ‘R’ by means of the HRPM, Human Resource Predictive Model. This ‘Requirement’ number will indicate whether there is a balanced workforce (zero), whether additional employees are needed (positive number), or whether there is an excess manpower situation (negative number); any of these numbers will give the organization necessary information for crafting a strategic human resources master plan. HR analysis and decisions on recruitments, dismissals, skillset-role matching, etc. can be significantly impacted by means of this model, as it gives a scientific reference point for all decision making.

5.2 Future Work

Successful human resource planning involves a deep understanding of human nature and human resource allocation. This thesis has focused on the prediction of human behavior regarding resignation and retirement, employee withdrawal forecasting, demand estimation, and workforce allocation. Although the allocation part is calculated based on a human resource predictive model, it does not consider the cost of human transactions, training for new hires, or layoff compensation. Workforce manipulation is not always easily done. Eliminating workers sometimes costs an organization more than money. For example, Division A of an organization has too few employees and Division B has too many. The question is “Is it economically viable to transfer five employees of compatible skill-sets from Division B to Division A instead of getting rid of five people in Division B and hiring five new people for Division A?”

To answer the question, operational research should be performed based on cost and working skill constraints. This will give the management team an idea about their workforce situation and financial position. Besides, this prospective model could come up with a workforce transaction strategy, giving users planning data to be able to maintain an appropriate number of employees at a minimum total operational cost.

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APPENDICES

Appendix 1

Withdrawal Prediction Coefficients for Manager

Manager	Employee Information					Age Range Matrix		
	Gender	Retirement Point	Year of Service (YCS)	Age	Salary Ranking	Age<41	Age between 41-56	Age >56
Eligible	-0.31543				-0.09976	-0.4315918	-0.7901729	
Ineligible	0.764158	-0.0170578		0.095276	-0.06896			

Withdrawal Prediction Coefficients for Manager (con't)

Manager	Quarter Matrix				Economy Condition		Interaction	cons.
	Q1	Q2	Q3	Q4	Delta(NYSE)	Unemployment Rate	ln (Age*YCS)	
Eligible		-0.2104207	-0.5701186	-0.72326	0.210748	-0.040476	0.2039285	-3.9628
Ineligible		-1.215475	-0.4336402	-1.35911	2.338475	-0.0375599		-6.99203

Withdrawal Prediction Coefficients for Craftsman

Craftsman	Employee Information					Age Range Matrix		
	Gender	Retirement Point	Year of Service (YCS)	Age	Salary Ranking	Age<41	Age between 41-56	Age >56
Eligible	1.355721				-0.8972222	-0.67955	-0.81867	
Ineligible	-0.31543				-1.050649			

Withdrawal Prediction Coefficients for Craftsman (con't)

Craftsman	Quarter Matrix				Economy Condition		Interaction	cons.
	Q1	Q2	Q3	Q4	Delta(NYSE)	Unemployment Rate	ln (Age*YCS)	
Eligible	1.693403	0.633023	0.5718343		2.278822	-0.00969	0.689514	-0.43939
Ineligible	0.709912		-1.400859	-2.24621	8.513285			7.211495

Appendix 2

Program Source Code in Microsoft Excel Marco

```
Dim ret As Integer

Sub UnSelectCurrentArea()
   Dim Area As Range
   Dim RR As Range

   For Each Area In Selection.Areas
      If Application.Intersect(Area, ActiveCell) Is Nothing Then
         If RR Is Nothing Then
            Set RR = Area
         Else
            Set RR = Application.Union(RR, Area)
         End If
      End If
   Next Area
   If Not RR Is Nothing Then
      RR.Select
   End If
End Sub

Function func_reset(sheetn As String, col As String)
 ' MsgBox (Range("P1").Value)
   Dim tmp_title As String
   Sheets(sheetn).Select
   tmp_title = Range(col & "1").Value
   Columns(col & ":" & col).Select
   Selection.ClearContents
   Range(col & "1").Select
   ActiveCell.FormulaR1C1 = tmp_title
   'ret = UnSelectCurrentArea()

End Function

Function func_col_reset(sheetn As String, col As String, fomular As String)

  ' keep Formula
   Sheets(sheetn).Select
   Dim fom As String
```

```
    fom = Range(col & "2").Formula

      ' clear & put title
    ret = func_reset(sheetn, col)

    Dim str As String
    Dim coln As String
    Dim counter As Integer
    str = col
    coln = col & "2"
    Range(coln).Select
    'ActiveCell.Formula = fomular
    ActiveCell.Formula = fom
    Range(coln).Select
    counter = Application.WorksheetFunction.CountA(Range("A:A"))
    str = str & counter
    Sheets(sheetn).Select
    Selection.AutoFill Destination:=Range(coln & ":" & str), Type:=xlFillDefault
   ' ret = UnSelectCurrentArea()

End Function

Function clone_col(wb As String, SheetSRC As String, SheetDST As String, colSRC
As String, ColDST As String)
    " Clone sheet 1
    " A:A


    Workbooks(wb).Activate
    Sheets(SheetDST).Select
    Columns(ColDST & ":" & ColDST).Select
    Selection.ClearContents
    Sheets(SheetSRC).Select
    Columns(colSRC & ":" & colSRC).Select
    Selection.Copy
    Sheets(SheetDST).Select
    Columns(ColDST & ":" & ColDST).Select
    ActiveSheet.Paste
    Application.CutCopyMode = False
    Columns(ColDST & ":" & ColDST).Select
    'ret = UnSelectCurrentArea()
End Function

Sub test()
   ' Dim fname As String
```

```
   ' fname = ThisWorkbook.Name

End Sub


Sub Generate()
'
' Generate Macro


    Dim fname As String
    fname = ThisWorkbook.Name
    Dim str As String
    Dim RAW As String
    Dim RAWfname As String
    RAWfname = "RAW.xlsx"
   ' Full path and name of file.
    RAW = (ActiveWorkbook.Path) & "\" & RAWfname
    Application.Workbooks.Open (RAW)

    " Clone sheet 1
    " A:A
    Windows(fname).Activate
    Sheets("data").Select
    Columns("A:A").Select
    Selection.ClearContents
    Windows(RAWfname).Activate
    ActiveWindow.WindowState = xlNormal
    ActiveWindow.WindowState = xlNormal
    Columns("A:A").Select
    Selection.Copy
    Windows(fname).Activate
    Sheets("data").Select
    Columns("A:A").Select
    ActiveSheet.Paste
    " Clone sheet 1
    " B:B
    Sheets("data").Select
    Columns("B:B").Select
    Selection.ClearContents
    Windows(RAWfname).Activate
    ActiveWindow.WindowState = xlNormal
    ActiveWindow.WindowState = xlNormal
    Columns("B:B").Select
    Selection.Copy
```

```
Windows(fname).Activate
Sheets("data").Select
Columns("B:B").Select
ActiveSheet.Paste
" Clone sheet 1
" C:C
Sheets("data").Select
Columns("C:C").Select
Selection.ClearContents
Windows(RAWfname).Activate
ActiveWindow.WindowState = xlNormal
ActiveWindow.WindowState = xlNormal
Columns("C:C").Select
Selection.Copy
Windows(fname).Activate
Sheets("data").Select
Columns("C:C").Select
ActiveSheet.Paste
" Clone sheet 1
" E:E
Sheets("data").Select
Columns("E:E").Select
Selection.ClearContents
Windows(RAWfname).Activate
ActiveWindow.WindowState = xlNormal
ActiveWindow.WindowState = xlNormal
Columns("D:D").Select
Selection.Copy
Windows(fname).Activate
Sheets("data").Select
Columns("E:E").Select
ActiveSheet.Paste
" Clone sheet 1
" F:F
Sheets("data").Select
Columns("F:F").Select
Selection.ClearContents
Windows(RAWfname).Activate
ActiveWindow.WindowState = xlNormal
ActiveWindow.WindowState = xlNormal
Columns("E:E").Select
Selection.Copy
Windows(fname).Activate
Sheets("data").Select
Columns("F:F").Select
```

```
ActiveSheet.Paste


' E+F
Windows(fname).Activate
ret = func_col_reset("data", "D", "=E2+F2")

' diff and ur

' diff_nyse
Windows(fname).Activate

ret = func_reset("DATA", "O")

Range("O2").Select
Windows(RAWfname).Activate
Range("I7").Select
Selection.Copy
Windows(fname).Activate
Range("O2").Select
ActiveSheet.Paste
Application.CutCopyMode = False
str = "O"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
Sheets("data").Select
Selection.AutoFill Destination:=Range("O2:" & str), Type:=xlFillDefault

' ur

ret = func_reset("DATA", "P")

Range("P2").Select
Windows(RAWfname).Activate
Range("I8").Select
Selection.Copy
Windows(fname).Activate
Range("P2").Select
ActiveSheet.Paste
Application.CutCopyMode = False
str = "P"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
Sheets("data").Select
Selection.AutoFill Destination:=Range("P2:" & str), Type:=xlFillDefault
```

```
Windows(RAWfname).Activate
Dim quarter As Integer
Windows(RAWfname).Activate
quarter = Range("I1").Value


Windows(fname).Activate
Sheets("data").Select
Columns("G:G").Select
Selection.ClearContents

Range("G1").Select
ActiveCell.FormulaR1C1 = "qone"

Columns("H:H").Select
Selection.ClearContents

Range("H1").Select
ActiveCell.FormulaR1C1 = "qtwo"

Columns("I:I").Select
Selection.ClearContents

Range("I1").Select
ActiveCell.FormulaR1C1 = "qthr"

Columns("J:J").Select
Selection.ClearContents
Range("J1").Select
ActiveCell.FormulaR1C1 = "qfor"

Windows(fname).Activate
Range("G2").Select
If quarter = 1 Then
   ActiveCell.FormulaR1C1 = 1
Else
   ActiveCell.FormulaR1C1 = 0
End If

Range("H2").Select
If quarter = 2 Then
   ActiveCell.FormulaR1C1 = 1
Else
   ActiveCell.FormulaR1C1 = 0
```

```
End If

Range("I2").Select
If quarter = 3 Then
    ActiveCell.FormulaR1C1 = 1
Else
    ActiveCell.FormulaR1C1 = 0
    End If

Range("J2").Select
If quarter = 4 Then
    ActiveCell.FormulaR1C1 = 1
Else
    ActiveCell.FormulaR1C1 = 0
End If

If quarter > 4 Then
   MsgBox ("ERROR")
End If

Windows(fname).Activate
str = "G"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
Sheets("data").Select
Range("G2").Select
Selection.AutoFill Destination:=Range("G2:" & str), Type:=xlFillDefault

str = "H"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
Sheets("data").Select
Range("H2").Select
Selection.AutoFill Destination:=Range("H2:" & str), Type:=xlFillDefault

 str = "I"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
Sheets("data").Select
Range("I2").Select
Selection.AutoFill Destination:=Range("I2:" & str), Type:=xlFillDefault

 str = "J"
count = Application.WorksheetFunction.CountA(Range("A:A"))
str = str & count
```

```
    Sheets("data").Select
    Range("J2").Select
    Selection.AutoFill Destination:=Range("J2:" & str), Type:=xlFillDefault

   'K
  '  ret = func_reset("DATA", "K")
    ret = func_col_reset("DATA", "K", "=IF((F2+E2)>=85,1,0)")
    'Q Jobrank
  '  ret = func_reset("DATA", "Q")
    ret = func_col_reset("DATA", "Q", "=VLOOKUP(B2,'Job Title
Convertion'!$A$1:$B$35,2,FALSE)")
    'R lagexysc
  '  ret = func_reset("DATA", "R")
    ret = func_col_reset("DATA", "R", "=LN(E2*F2)")
    'S Eli =IF(OR(F2>=65,D2>=85),1,0)
  '  ret = func_reset("DATA", "S")
    ret = func_col_reset("DATA", "S", "=IF(OR(F2>=65,D2>=85),1,0)")
    'T Group
=IF(S2=0,IF(Q2>=1,IF(Q2<=10,"Res_Lo",IF(Q2>=11,IF(Q2<=14,"Res_Up")))),IF(
Q2>=1,IF(Q2<=10,"Ret_Lo",IF(Q2>=11,IF(Q2<=14,"Ret_Up")))))
   ' ret = func_reset("DATA", "T")
    ret = func_col_reset("DATA", "T",
"=IF(S2=0,IF(Q2>=1,IF(Q2<=10,""Res_Lo"",IF(Q2>=11,IF(Q2<=14,""Res_Up"")))
),IF(Q2>=1,IF(Q2<=10,""Ret_Lo"",IF(Q2>=11,IF(Q2<=14,""Ret_Up"")))))")
    'U SEX
  '  ret = func_reset("DATA", "U")
    ret = func_col_reset("DATA", "U",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",U2)-
CELL(""col"",$T2)+1,FALSE)*C2")
    'V point
  '  ret = func_reset("DATA", "V")
    ret = func_col_reset("DATA", "V",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",V2)-
CELL(""col"",$T2)+1,FALSE)*D2")
    'W ysc
   ' ret = func_reset("DATA", "W")
    ret = func_col_reset("DATA", "W",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",W2)-
CELL(""col"",$T2)+1,FALSE)*E2")
    'X age
   ' ret = func_reset("DATA", "X")
    ret = func_col_reset("DATA", "X",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",X2)-
CELL(""col"",$T2)+1,FALSE)*F2")
    'Y qone
```

```
  ' ret = func_reset("DATA", "Y")
   ret = func_col_reset("DATA", "Y",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",Y2)-
CELL(""col"",$T2)+1,FALSE)*G2")
   'Z qtwo
 '  ret = func_reset("DATA", "Z")
   ret = func_col_reset("DATA", "Z",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",Z2)-
CELL(""col"",$T2)+1,FALSE)*H2")
   'AA qthr
  ' ret = func_reset("DATA", "AA")
   ret = func_col_reset("DATA", "AA",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AA2)-
CELL(""col"",$T2)+1,FALSE)*I2")
   'AB qfor
 '  ret = func_reset("DATA", "AB")
   ret = func_col_reset("DATA", "AB",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AB2)-
CELL(""col"",$T2)+1,FALSE)*J2")
   'AC p85
 '  ret = func_reset("DATA", "AC")
   ret = func_col_reset("DATA", "AC",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AC2)-
CELL(""col"",$T2)+1,FALSE)*K2")
   'AD grp1_age
  ' ret = func_reset("DATA", "AD")
   ret = func_col_reset("DATA", "AD",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*L2")
   'AE grp2_age
 '  ret = func_reset("DATA", "AE")
   ret = func_col_reset("DATA", "AE",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*M2")
   'AF grp3_age
 '  ret = func_reset("DATA", "AF")
   ret = func_col_reset("DATA", "AF",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*N2")
   'AG diff_nyse
 '  ret = func_reset("DATA", "AG")
   ret = func_col_reset("DATA", "AG",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*O2")
   'AH ur
```

```
  '  ret = func_reset("DATA", "AH")
    ret = func_col_reset("DATA", "AH",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*P2")
    'AI jobrank
  '  ret = func_reset("DATA", "AI")
    ret = func_col_reset("DATA", "AI",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*Q2")
    'AJ lagexyse
  '  ret = func_reset("DATA", "AJ")
    ret = func_col_reset("DATA", "AJ",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)*R2")
    'AK cons.
  '  ret = func_reset("DATA", "AK")
    ret = func_col_reset("DATA", "AK",
"=VLOOKUP($T2,Logit_Parameter!$A$2:$R$5,CELL(""col"",AD2)-
CELL(""col"",$T2)+1,FALSE)")
    'AL L
  '  ret = func_reset("DATA", "AL")
    ret = func_col_reset("DATA", "AL", "=SUM(U2:AK2)")
    'AM e^L
  '  ret = func_reset("DATA", "AM")
    ret = func_col_reset("DATA", "AM", "=2.71828183^AL2")
    'AN p(x)
  '  ret = func_reset("DATA", "AN")
    ret = func_col_reset("DATA", "AN", "=AM2/(1+AM2)")
```

Appendix 3

Comparison Table between Predicted HC' and Actual HC'

Time Horizon		38			39			40			41		
Job Group	**Job Title**	**Predicted HC'**	**Actual HC'**	**%Error**	**Predicted HC'**	**Actual HC'**	**%Error**	**Predicted HC'**	**Actual HC'**	**%Error**	**Predicted HC'**	**Actual HC'**	**%Error**
Manager	M1	30.32	29	4.57%	29.72	29	2.50%	28.83	29	-0.58%	26.99	29	-6.92%
	M2	27.56	28	-1.56%	27.87	28	-0.47%	27.92	28	-0.29%	26.55	28	-5.17%
	M3	12.90	13	-0.73%	12.97	13	-0.23%	12.98	13	-0.14%	12.70	10	26.98%
	M4	1.00	1	-0.10%	1.00	1	-0.08%	1.00	1	-0.05%	1.00	1	-0.14%
Craftsman	L1	100.37	102	-1.59%	107.22	106	1.15%	104.88	105	-0.12%	101.66	102	-0.33%
	L2	0.99	1	-1.07%	0.99	1	-0.75%	0.99	1	-0.66%	0.99	1	-1.42%
	L3L	15.85	16	-0.96%	17.86	17	5.04%	16.90	17	-0.62%	16.73	17	-1.60%
	L4	30.58	31	-1.37%	30.52	31	-1.55%	30.70	31	-0.98%	32.03	33	-2.95%
	L5	52.42	53	-1.09%	52.32	53	-1.27%	52.59	53	-0.78%	51.64	53	-2.57%
	L6	57.35	56	2.41%	56.40	55	2.55%	55.59	55	1.07%	53.85	55	-2.09%
	L7	27.81	28	-0.69%	27.85	28	-0.54%	28.87	29	-0.44%	31.68	30	5.60%
	L8	81.18	81	0.22%	82.83	81	2.26%	83.41	84	-0.71%	81.60	82	-0.48%
	L9	388.62	390	-0.35%	401.55	403	-0.36%	412.46	413	-0.13%	404.81	408	-0.78%
	L10	115.04	114	0.92%	118.97	119	-0.03%	119.33	119	0.28%	117.04	113	3.57%

VITA

Tachapon Saengsureepornchai was born January 9th 1983, in Chanthaburi, Thailand and attended Benjamarachutis School. He later moved to Bangkok, Thailand and attended Kasetsart University, where he obtained a Bachelor's of Engineering in Industrial Engineering in May 2004. He then worked as an Industrial Engineer at Fabrinet Co., Ltd. for two years. He joined the University of Tennessee – Knoxville in the fall of 2008 and began working towards his Master of Science in Industrial Engineering under the tutelage of Dr. Rupy Sawhney. During his master's program, he has worked as a Graduate Research Assistant under Dr. Sawhney on many interesting industrial projects.