This paper discusses the concept of dynamic help desk resource modeling for a major Information Technology Enterprise Resources Planning (ERP) system. The methodology discussed herein utilizes regression analysis to project the resource requirements for a three-tiered help desk system, shown below in Figure 1, based on a number of factors including system user population and maturity. This study utilizes data and direct observations from the implementation of a help desk system serving the largest Federal ERP implementation in history. This ERP system was deployed to a number of client organizations over time, resulting in a discrete step function increase in ERP system user populations with each deployment.

The help desk system studied utilizes a three-tier structure for ticket routing and processing. The following establishes the typical escalation process for ticket items entering the help desk: Tier 1 answers the initial call from the user, creates a ticket for tracking, performs the initial triage, and escalates the issue to the appropriate next level (Tier 2 or Tier 3) as required.

This paper argues that help desk staffing requirements are a function of more than just total number of system users – other factors include user activity level, user maturity, system maturity, system complexity, and implementation stage.

The paper explains a methodology to understand the shifts in help desk ticket volumes and resource requirements over time as the users, system, and help desk staff mature. The model discussed in this paper predicts help desk requirements with demonstrated certainty, giving decision makers sufficient information to project future costs, ensure optimum funding levels, and plan functional staff resource levels dynamically over time. Furthermore, this dynamic staffing ability allows program management to vary staffing levels, and their resulting cost impacts, to make optimum use of these valuable resources.
The traditional approach to this problem would involve using either a step function (e.g., 1 additional help desk FTE for every additional increment of 500 users) or a parametric estimate (e.g., total number of system users multiplied by x%). For the system that was studied in this example, both of these approaches would have underestimated the number of resources required soon after implementation when help desk call volumes are higher, and overestimated the number of resources required after implementation when users have adjusted to the new system and the system itself has matured. The result of such an approach would be insufficient resources in the near-term and overinflated sustainment costs in the long-term. This fixed capacity approach is shown in Figure 2.

Data Observations
Figure 3 shows the number of help desk tickets that were submitted each week for the 1st of the 6 planned system deployments. The system went “live” in December of 2007 and the spike in help desk tickets occurred the week of system go-live. In analyzing the data from the initial deployment, it was clear that there were 3 distinct periods that characterized the behavior of the data:
Data Analysis and Modeling Techniques

After plotting the data and identifying the three distinct deployment stages, Herren’s team of analysts developed a method for estimating the required help desk staffing for the five remaining deployments. At the time, the only data available about the remaining deployments was the number of system users and the planned go-live dates. The team also interviewed technical subject matter experts who believed that many system defects and training issues experienced during the first deployment would be addressed prior to the following deployments and would reduce the overall number of help desk tickets. These SMEs also believed that the help desk resources would become more efficient at closing tickets over time as they gained familiarity with common system issues and the appropriate resolution.

In order to determine the number of resources required to support the help desk, the model had to predict the number of incoming tickets and the expected closure rate for each ticket. The number of incoming tickets was believed to be primarily driven by the number of users, the maturity of the system, and the deployment phase (pre go-live, go-live, or sustainment).

Since the number of incoming help desk tickets is largely dependent on the number of users in the system, the first step in the analysis was to normalize the data based on the total user count. This was accomplished by dividing the total number of tickets submitted by the total number of users to obtain the number of tickets submitted per week per user.

After the data was normalized and plotted for each stage of deployment, a regression equation was used to determine the predicted number of help desk tickets that each user would submit per week based on the number of weeks prior to or after the go-live date.

As discussed previously, another variable was added to account for the projected reduction in help desk tickets during each subsequent deployment as predicted by the technical SMEs based on system maturity.

We represent the equations associated with each deployment phase using the variable Pi where i equals:

- 1 for the Pre-Go Live stage
- 2 for the Go-live stage
- 3 for the sustainment stage
Data Analysis and Modeling Techniques

Pi is determined by comparing the go-live date to the week being calculated in the model. It is set to equal zero for any week in the model that is more than 30 weeks prior to the go live date. All variables required to project the number of tickets per week are described below:

\[ T_n = \text{Projected number of tickets per week} \]
\[ P_i = \text{Deployment phase equation} \]
\[ d = \text{Deployment 1 to 6 as depicted in Figure 1} \]
\[ U_d = \text{Total number of users per deployment} \]
\[ S_d = \text{The estimated percentage reduction in the number of tickets from the initial deployment based on system maturity where } 0 < S \leq 1 \text{ for deployment, } d. \]

\[ T_n = \sum_{d=1}^{6} (U_d \times P_i \times (1 - S_d)) \]

In addition to projecting the number of help desk tickets that will be submitted each week, the team also determined the service rate for closing help desk tickets. Since the desired output of the model is the number of help desk FTEs required to support the users, the team determined the average number of help desk tickets that were closed by each help desk FTE per week. This was calculated by simply dividing the number of help desk tickets closed each week by the number of FTEs that were working on the help desk during that week. We will represent this service rate (expected # of tickets closed per FTE per week) by the variable R.

Based on feedback from the technical team, the team also incorporated an improvement in service rate over time to account for the anticipated learning curve for the help desk resources. So the anticipated service rate is represented by the below equation:

\[ \text{Adjusted Service Rate} = R \times (1 + L_n) \]

Where \( L \) represents the estimated percentage increase in the service rate for week \( n \) and \( 0 < L \leq 1 \).

Finally, the projected number of required FTEs for week \( n \) is calculated by dividing the projected number of tickets (\( T_n \)) by the adjusted service rate

\[ \text{Required Help desk FTEs for week } n = \frac{T_n}{R \times (1 + L_n)} \]

To request a full study, please email Peter Banfield at peter.banfield@jlha.com