

DETC2012-71554

MODELING THE OBSOLESCENCE OF CRITICAL HUMAN SKILLS NECESSARY FOR SUPPORTING LEGACY SYSTEMS

Peter Sandborn, Varun J. Prabhakar, and Abisola Kusimo

CALCE Center for Advanced Life Cycle Engineering
Department of Mechanical Engineering
University of Maryland
College Park, MD 20742

ABSTRACT

Obsolescence of human skills impacts the support of long field life systems. Human skills obsolescence is a growing problem for organizations as they try to estimate and mitigate the effects of an aging workforce with specialized (and possibly irreplaceable) skill sets. Difficulties with skills obsolescence have been reported in a number of industries including industrial controls, aerospace, and military systems, all product sectors that must support critical systems for 20-30 years or longer.

Common workforce planning models do not generally address the obsolescence of skills. Rather, they implicitly assume lost human resources are always replenishable. Nearly all of the existing research associated with the obsolescence of skills focuses on the opposite of the problem addressed in this paper, i.e., workers have skills that are obsolete and therefore need to be retrained in order to be employable. Alternatively, this paper addresses the lack of workers with the necessary skill set and the inability to replace them. This paper describes a model for the obsolescence of skills and skilled worker retention. This research provides a way to quantitatively address the problem of skills obsolescence and provides a basis upon which to estimate the cost of future system support.

Keywords: Maintenance, experience, resources, hiring rate, obsolescence, DMSMS, workforce planning

1 INTRODUCTION

Manufacturing and support organizations wish to have a secure skill pool that allows for full functionality and efficiency; however in reality the skill pool, skill level and the number of available employees tends to fluctuate, requiring careful management and forecasting to ensure that overall support is not disrupted or delayed. There are many types of mission, safety and infrastructure critical systems that have very long field support lives. Examples include military systems, industrial and transportation control systems, and communications infrastructure. Technology and part obsolescence are common

problems faced by these systems [1], e.g., the inability to procure spare parts to maintain the systems. This problem is commonly referred to as Diminishing Manufacturing Sources and Material Shortages (DMSMS). Obsolescence, however, is not solely a hardware problem; it also impacts software [2] and the human skills necessary to maintain long field life systems. Human skills obsolescence is a growing problem for organizations that must support mission, safety and infrastructure critical systems as they try to estimate and mitigate the effects of an aging work-force with specialized (and possibly irreplaceable) skill sets. In the context of human skills, "obsolescence" implies that the replenishment of skills is not possible or partial at best. If the skills are replenishable, multiple new hires may be needed to reproduce the level of work of each experienced employee that leaves the organization.

The motivation behind the research described in this paper was the age distribution of engineers supporting a legacy control system used in the chemical and material production industry. The mean age of employees is currently 56 and increasing as it has been difficult to retain new people to support the legacy system as younger employees relocate to other sectors and job opportunities that they perceive as having better long-term job prospects.¹ Similar difficulties have been reported in a number of industries including the Healthcare Industry [3] and other enterprises [4]. The problem is particularly relevant with organizations that must support critical systems for long periods of time, e.g., 20-30 years or longer (so called sustainment-dominated systems, [5-6]). With many employees approaching the average retirement age, a general hiring rate model for replacement and a human support risk cost-model was needed to assess the severity of the problem. The situation posed a major question for the company, how will the obsolescence of skills and the possible inability to replace these skills affect the cost of supporting the legacy system for another 10-20 years?

¹ This paper does not address the particular reasons that the retention of younger engineers is insufficient to replenish the current skills pool.

The majority of past research in skill obsolescence addresses the opposite problem wherein workers' skills are no longer useful or become outdated as a result of automation and the rapid growth in technology (e.g., [7-11]). These works deal with ways to mitigate skill "decay" over time for a given workforce.

In this paper, we define "worker obsolescence" to mean that workers' skills are no longer useful while "skill obsolescence" refers to workers who have particular skills that are lost as those workers die, retire or leave the organization. Although it is a common problem, very little existing work is focused on the most able workers being the oldest (in our particular case) and the most valuable. The analytical techniques presented by Bohlander and Snell [12] modeled a similar situation, however, they do not include the attrition or the costs associated with the varying availability of the workers. Bordoloi [13] developed a model for workers that are at different skill levels entering and exiting a company; additionally, the rate at which the employer gains and loses employees is also taken into account in their planning model. However, Bordoloi [13] stops short of estimating the experience in the pool as a function of time and thereby determining the impact that skills obsolescence has on the support of systems. Huang *et al.* [14] developed a planning model using a computer simulation where the goal was to determine an ideal hiring rate based on the different levels of skill that workers had. Although this model uses workforce simulation and calculates an ideal hiring rate, this model does not account for the costs incurred by the availability of workers in their determination of an ideal hiring rate.

Holt [15] points out that the traditional understanding of a workforce has been in terms of the "physical sum of people employed," which is the basis for most common workforce planning models. A more useful approach is to observe workers in an organization as assets with varying skill levels. Holt [15] defines human capital investment as the "total amount and quality of talent, knowledge, expertise, and training that these workers possess." Holt [15] minimizes cost while maintaining balanced levels of human capital. However, the model is based on categorizing workers by "classes" wherein all workers in a class share similar attributes. The Holt model also lacks aging and age-related effects of individual workers over time.

This paper is concerned with the variation of the cumulative skill pool and its relation to cost as a function of time. The training of new workers takes time, incurs costs, and there is no guarantee that the workers will not be lost before they are completely trained. The ultimate questions that need to be answered are "what will today's skills pool look like after 'x' years?" and "what impact will the skills pool have on my ability to continue to support a system?" The model described in this paper offers a projection for the future and a way to quantify cumulative experience versus the influx of new workers and their departures.

The next section describes the development of the human skills replenishment model. This is followed by a case study from the chemical manufacturing industry.

2 ESTIMATION OF THE HUMAN SKILLS POOL AND THE REPLENISHMENT OF EXPERIENCE

The model presented in this paper estimates the number of skilled employees (pool size) and the combined (cumulative) experience of the skills pool in order to determine the resources that will be available to maintain a long life cycle legacy system or family of systems. The cumulative experience of the skills pool impacts the time (and thereby the cost) to perform the necessary maintenance activities to sustain a system.² In order to assess pool size and experience, we have to track (or forward calculate) the experience of the people in the pool over time based on when they were hired while accounting for age related loss. In this section, a human skills replenishment model is developed to determine the cumulative experience in the skills pool as a function of time and a fixed hiring rate. We also determine the required hiring rate over time in order to preserve a constant cumulative experience throughout a specified system support life.

The level of experience within the skills pool varies over time and can be determined from the following: 1) new hires added to the skills pool, 2) attrition rate or loss of skilled employees due to job changes, promotions, retirement, etc., and 3) accounting for the varying skill levels of the people in the pool.

Initially, we assume that the organization's policy dictates the hiring rate, H , resulting in a varying skills pool that can be modeled over time. Since the data (see Section 3) is only available on an annual basis, we utilize discrete time steps, i , of 1 year throughout these analyses; however, i can be any arbitrary unit of time. Let H be the new hires per year as a fraction of the pool size at the start of the analysis period ($i = 0$). Let f_C be the probability distribution function (PDF) of age for the current skills pool, f_H be the PDF of age for new hires, and f_L be the PDF of age for people exiting the pool (attrition). Then, $N_i(a)$ is the net frequency of people in the pool of age a during year i , given by,

$$N_i(a) = [N_{i-1}(a-1) + Hf_H(a)](1 - f_L(a)) \quad (1)$$

where, i is the number of years from the start of the analysis period. Note that at $i = 0$, $N_0(a) = f_C(a)$ corresponding to the current distribution of worker age in the skills pool. Therefore, the cumulative net frequency³ of people in the skills pool, $N_{NET\%}$, in year i is given by,

² The time to perform maintenance to support a system is a significant cost driver for availability-centric systems. Availability is the ability of a service or a system to be functional when it is requested for use or operation and is determined by the combination of reliability and maintainability. For many systems, the cost of unavailability is very large, e.g., high-volume manufacturing, airlines, medical devices, etc.

³ We use the term "net frequency" because $N_{NET\%}(i)$ can be greater than 1. This can occur when the number of new hires exceeds the number of people exiting the pool.

$$N_{NET\%}(i) = \sum_{a=y}^r N_i(a) \quad (2)$$

where, r is retirement age and y is the age of the youngest employee in the skills pool. The age of the youngest worker, y , corresponds to the age of the youngest worker at the start of the analysis period (from f_C) or the youngest worker that is hired during the analysis period (from f_H). This model assumes that a mandatory retirement age, r , exists. Early retirement along with other reasons for loss in skilled employees are assumed to be captured in the PDF for attrition, f_L . Conversely, the PDF of retention, f_R for the skills pool can be estimated annually by, $f_R(a) = 1 - f_L(a)$.

Estimating the size of the pool over time is necessary but not sufficient to capture the ability to support a system into the future because not all workers in the pool have an equivalent level of experience and therefore an equivalent level of “value” to sustaining the system. The following analysis estimates cumulative experience in order to track the true value of the pool of skilled workers where “experience” is the length of time that a worker has spent in a particular position. The cumulative experience of the pool in year i , E_i , can be calculated using,

$$E_i = \sum_{a=y}^r aR_E N_i(a) \quad (3)$$

where, R_E = ratio of experience to age. Note, “experience” is an arbitrary unit of time. E_i is only used in the model to determine the change in cumulative experience from the initial condition. In the analyses and case study that follows, experience is measured in “years”.

The cumulative experience of the pool in year i as a percentage of the current pool experience, E_0 can be calculated as,

$$E_{\%i} = 100 \frac{E_i}{E_0} \quad (4)$$

Using the cumulative experience, the time to perform maintenance in year i is given by,

$$T_i^m = 100 \frac{T_0^m}{E_{\%i}} \quad (5)$$

where, T_0^m is the time to perform maintenance with a skills pool having E_0 experience at time $i = 0$. Equation (5) can be used to predict the time to perform maintenance and thereby the cost of maintenance as a function of years into the future (see Section 3.1). The time increase modeled in (5) is due to several factors: 1) less experienced workers may simply require more time to perform the task (learning curve effects), and/or 2) the number

of workers who can perform the required maintenance activity is smaller, so they may not (for example) be available at every site, i.e., they may have to be flown in from a different location.

All of the development so far assumes a fixed hiring rate that may or may not be sufficient to maintain the current level of experience. Finally, the model can be used to estimate the hiring rate required to maintain the current level of experience over the system’s support life. The required hiring rate (assuming hiring is possible) in year i , H_i , can be calculated as,

$$H_i = \left[\frac{N_i(a)}{(1 - f_L(a))} - N_{i-1}(a-1) \right] \left(\frac{1}{f_H(a)} \right) \quad (6)$$

subject to the constraint,

$$E_{\%i} = 100 \frac{E_i}{E_0} = 100\% \quad (7)$$

The next section presents an example case study that uses the methodology presented in this section.

3 CASE STUDY

This section presents a case study that implements the model developed in Section 2 with data from a chemical product manufacturing organization. The PDF of age for the current skills pool, f_C , is shown in Figure 1. The PDF of hiring age is shown in Figure 2. The PDF of age when workers exit the pool is shown in Figure 3. Weibull distributions representing f_C , f_H , and f_L are generated from data using the Maximum Likelihood Estimation (MLE) method. Fits using other distributions such as Gaussian, Beta, and Log-normal could also be considered based on tests for “goodness-of-fit” with respect to the available data. This analysis assumes that the distributions for f_H and f_L are static for the entire analysis period. The mandatory retirement age, r , is assumed to be 60 years at which workers are required

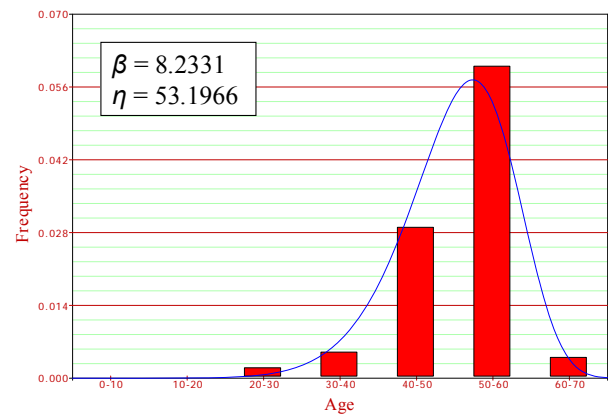


Figure 1 – Frequency for the age of workers in the current skills pool and the corresponding Weibull (2 parameter) PDF, f_C .

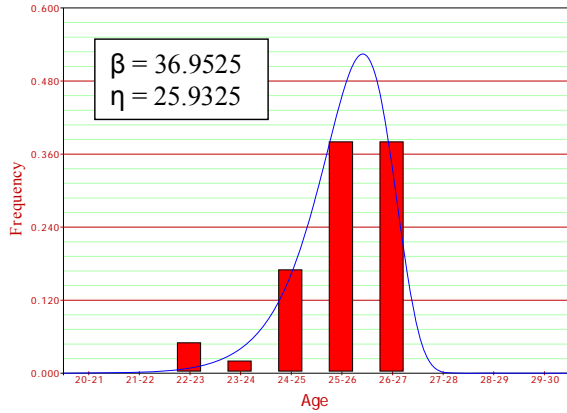


Figure 2 – Frequency for annual hiring age and its corresponding Weibull (2 parameter) PDF, f_H .

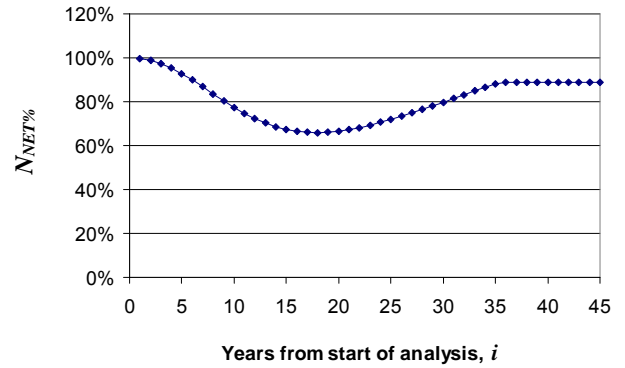


Figure 4 – Annual net pool size (as percentage of current pool size), $N_{NET\%}$.

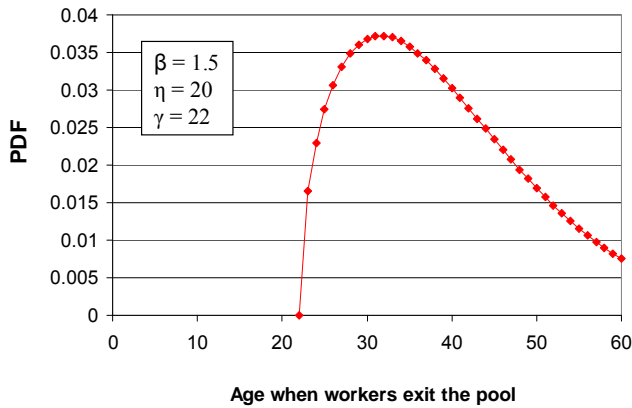


Figure 3 – Weibull (3 parameter) PDF for age when workers exit the pool, f_L .

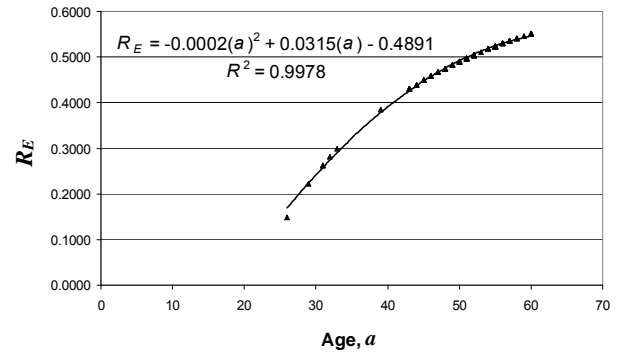


Figure 5 – Ratio, R_E , with respect to age, a . A curve fit of $R_E(a)$ using a 2nd degree polynomial is given in the plot.

to leave the skills pool.

Figure 4 shows $N_{NET\%}$, the net pool size (number of workers), over time as a fraction of the pool size at year 0. This example assumes a fixed 4% hiring rate, H , annually. Based on the assumed attrition rate and hiring rate, the skills pool is expected to decrease for 16 years to a minimum of 66% of the current pool size. The net pool size reaches a theoretical “steady state” of 84% after 38 years (i.e., hiring rate and attrition rate no longer cause the size of the pool to change). “Steady state” occurs because age distributions for both new hires and attrition (f_H and f_L) are static. The effect is a balance between an influx of new hires and loss due to attrition that begins when all employees in the current pool have passed the age of retirement (after year 38).

Figure 4 only partially describes the effect of the assumed hiring rate. A more accurate representation of the value of the skills pool is to assess the cumulative experience, $E\%$. To assess cumulative experience we need an estimate of R_E (the experience/age ratio). Data for employee age and experience are used to determine ratio, R_E , as a function of age, a , is shown in

Figure 5. Using (3) and (4), Figure 6 shows that the combined loss in employees to retirement and attrition over the first 17 years causes a decrease in cumulative experience to nearly 43% of the current value. This example case assumes that the maximum experience that can be achieved by any employee is 20 years (i.e., the employee’s value no longer increases beyond 20 years). This assumption is based on evidence that indicates the time taken to perform all related tasks does not decrease further for skilled workers with more than 20 years of experience for this case study; however, this assumption is not required for the methodology in this paper to be performed.

3.1 SKILLS OBSOLESCENCE IMPACT ON COST

To provide some context for the results developed in this example, Figure 7 shows the annual cost of supporting a legacy control system from the chemical and material production industry through year 2029 (over 2000 instances of the system require support in this case). The cost model used is a stochastic discrete event simulator that samples time-to-failure distributions for the components of the control system to obtain maintenance events (event dates and components that need

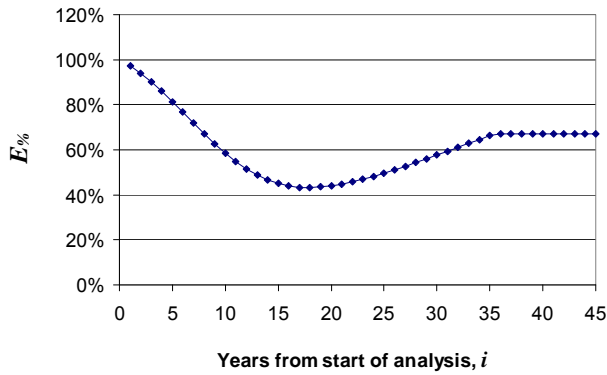


Figure 6 – Cumulative experience of the pool (as percentage of current pool experience), $E_{\%}$.

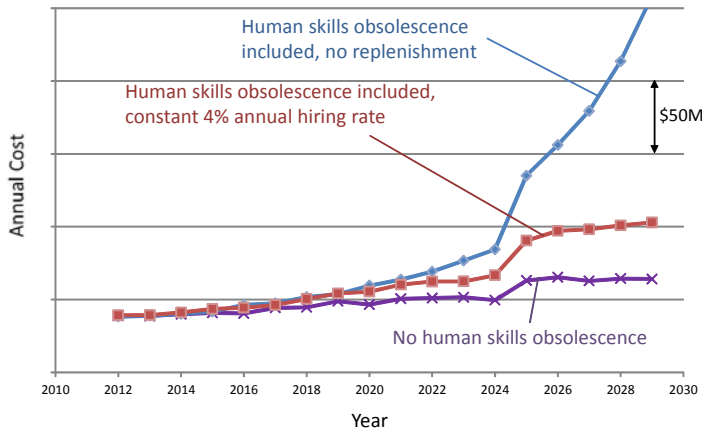


Figure 7 – Annual cost of supporting a legacy control system with and without skills obsolescence.

replacement). While the details of the cost model are beyond the scope of this paper, when a maintenance event occurs, the cost of performing the necessary maintenance action is modeled using,

$$C_i^m = C_i^p + \left[100 \frac{T_0^m}{E_{\%i}} \right] C_i^l \quad (8)$$

where the term in brackets is the maintenance time from (5), C_i^p is the cost of replacement part (if a replacement is needed) in the i th year and C_i^l is the cost of labor in the i th year. Both C_i^p and C_i^l are discounted to the i th year and C_i^p may include holding (inventory) costs if the part is obsolete in year i and was obtained in a lifetime buy at an earlier time.

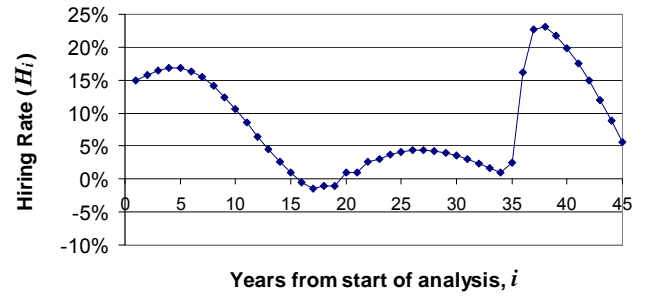


Figure 8 – Hiring rate over time, H_i , required to preserve the current cumulative experience.

Three results are shown in Figure 7. The figure shows that there is little effect of skill obsolescence prior to 2020, but after that the impact of the loss of skills becomes significant. Note, in year 2025 the availability of spares (hardware) also becomes a problem resulting in the step shown between years 2024 and 2025. The lowest curve in Figure 7 assumes that there is no human obsolescence ($E_{\%i} = 100$ for all i in (8)). Even in this case, the annual cost increases due to part obsolescence that results in lifetime buys of parts that tie up significant capital in pre-purchased parts and long-term holding costs. The middle curve assumes the level of human skills obsolescence assumed by the data in this case study with a 4% annual hiring rate ($H = 0.04$ for all i). As the results indicate, a 4% annual hiring rate (if possible) is not sufficient to mitigate the loss of skills and results in a nearly \$40M/year cost by increases 2030. The final case (highest cost curve) shown in Figure 7 assumes that no replenishment of lost skills is possible.

3.2 REQUIRED HIRING RATE

Assuming the lost skills are replenishable, we now wish to estimate the future hiring rate, H_i , required to preserve the current level of experience, E_0 , in the skills pool. The analysis identifies a solution⁴ for the system of equations (the objective function in (6) is subject to the constraint in (7)) to determine the annual hiring rate, H_i , needed to replenish the loss in cumulative experience as a result of attrition and retirement. The estimation of the required hiring rate can be performed at any point during the analysis or as frequently as needed to replenish the skills pool and maintain the desired experience level. For this example, the operation is repeated periodically at 1 year time steps until the end of the analysis period (end of the system's support life). Figure 8 shows results for hiring rate, H_i , as a function of the number of years from the start of the analysis. Figure 8 shows that a hiring rate of over 15% is required for the first 7 years and

⁴ The analysis implements the "goal seek" toolbox in MS Excel to solve for hiring rate, H_i . The goal seek function follows an iterative process to identify values that satisfy the required target conditions. The operation was observed to converge to the target value ($E_{\%} = 100\%$) with less than 0.1% uncertainty.

over 4% until year 13. The results in Figure 8 also show that the hiring rate becomes negative between year 16 and year 19. This occurs since the current solution process calculates H_i periodically utilizing information from previous time steps only. In order to satisfy the constraint in (7) and maintain the level of experience, $E\%$, at 100%, the required hiring rate prior to year 16 causes $E\%$ to overshoot 100%. This effect can only be counteracted by voluntarily reducing the pool size. Relaxing the constraint to maintain a minimum level of experience (rather than a fixed level of experience) can eliminate the need to voluntarily reduce the pool size; this method also allows flexibility when hiring rate is constrained.

4 SUMMARY AND DISCUSSION

The exigent nature of the skills obsolescence problem is that organizations may encounter this dilemma and without existing models that produce information in terms of cost impacts, the organization may struggle to move forward. Restated, the workforce planning problem that many organizations are facing is ensuring that they have the right number of people, with the right skills sets, in the right jobs, at the right time.

To address this problem, a model for the loss of critical skills necessary to support legacy systems has been developed. The model estimates the number of skilled employees (pool size) and the combined (cumulative) experience of the skills pool in order to determine the resources that will be available to maintain a long life cycle legacy system or family of systems. The cumulative experience of the skills pool impacts the time (and thereby the cost) to perform the necessary maintenance activities to sustain a system.

The model presented has only been used to assess support (maintenance) costs, but it could also be used to directly assess system availability as well (for systems subject to availability contracts such as performance-based logistics contracts, e.g., [16]).

Several simplifying assumptions have been made in the model described in this paper.⁵ We have assumed the age distributions of new hires and of workers exiting the pool are the same for the entire analysis period –these distributions may change over time. In our solution we have also assumed that everyone entering the pool has no experience – this may not be the case; some workers could enter the pool with relevant experience gained from other positions. Our solution also assumes that the only way workers gain experience is through years on the job. There may be other methods that can accelerate the rate at which workers become more experienced, e.g., knowledge bases created to capture the experience of older workers. A discrete time analysis is presented in this paper because the available data only exists on an annual basis, however, a continuous time solution could also be developed.

⁵ Although the model is based on historical distributions of the hiring age, exit age, and current age of workers in the pool, the model assumes that these distributions will remain the same over time. Performing uncertainty analysis would involve allowing these distributions to change over time, i.e., trending the distributions over time.

5 REFERENCES

- [1] Sandborn, P., 2008, "Trapped on Technology's Trailing Edge," *IEEE Spectrum*, 45(4), pp. 42-58.
- [2] Sandborn, P., 2007, "Software Obsolescence - Complicating the Part and Technology Obsolescence Management Problem," *IEEE Transactions on Components and Packaging Technologies*, 30(4), pp. 886-888.
- [3] Waldman, J., 2004, "Measuring Retention Rather Than Turnover: A Different and Complementary HR Calculus," *HR. Human Resource Planning*, 27(3).
- [4] Leibold, M., and Voelpel, S., 2006, *Managing the Aging Workforce: Challenges and Solutions*. John Wiley & Sons, New York, NY.
- [5] Sandborn, P. and J. Myers, J., 2008, "Designing Engineering Systems for Sustainment," *Handbook of Performability Engineering*, ed. K.B. Misra, Springer, pp. 81-103, London.
- [6] Sneed, H. M., 2002, "Planning the Reengineering of Legacy Systems," *IEEE Software*, 12(1), pp. 24-34.
- [7] De Grip, A., 2006, *Evaluating Human Capital Obsolescence*, Maastricht: Maastricht University.
- [8] Dubin, S. S., 1972, "Obsolescence of Lifelong Education," *American Psychologist*, 27, pp. 486-498.
- [9] Allen, J., and De Grip, A., 2004, *Skill Obsolescence Lifelong Learning and Labour Market Participation*, Research Centre for Education and the Labour Market, Maastricht: Maastricht University.
- [10] Arthur, W. J., Bennett, W. J., Stanush, P. L., and McNelly, T. L., 1998, "Factors that Influence Skill Decay and Retention: A Quantitative Review and Analysis," *Human Performance*, 11(1), pp. 57-101.
- [11] Hagman, J. D., 1980, *Effects of Training Schedule and Equipment Variety on Retention and Transfer of Maintenance Skill*, Alexandria, VA: U.S. Army Research Institute for Behavioral and Social Sciences, Research Report 1309.
- [12] Bohlander, G. W., and Snell, S. A., 2010, *Managing Human Resources*, 15th edition, Mason, Ohio: South-Western CENGAGE Learning
- [13] Bordoloi, S. K., 1999, "Flexibility, Adaptability and Efficiency in Dynamic Manufacturing Systems," *Journal of Production and Operations Management*, 8(2), pp. 133-150.
- [14] Huang, H.-C., Lee, L.-H., Song, H., and Eck, B. T., 2009, "SimMan - A Simulation Model for Workforce Capacity Planning," *Computers and Operations Research*, 36(8), pp. 2490-2497.
- [15] Holt, B., 2011, *Development of an Optimal Replenishment Policy for Human Capital Inventory*, Dissertation from the University of Tennessee Knoxville.

[16] Beanum R., 2006, "Performance-Based logistics and contractor support methods," Proceedings of the IEEE Systems Readiness Technology Conference (AUTOTESTCON).