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Tool

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Modeling for Manpower and Personnel Policy Analysis

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About This Tool

Researchers in the manpower and personnel programs within RAND often develop or employ personnel inventory models to generate research findings. These models are typically designed to predict stocks and flows of personnel inventories or, more commonly, to simulate potential outcomes as a function of alternative human resource management policies. This tool describes a sample of such efforts undertaken at RAND within the past several decades. Some models described in the tool are of historical significance. Others, by virtue of recent usage, can be accessed by current researchers, at least conceptually if not in actual operative form. The tool should be of interest to researchers at the formative stage of a project to help in visualizing potential analytic paths.

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Summary

Personnel inventory modeling and related methods form the backbone of many human capital management analyses. RAND has an extensive history in the development and application of these methods. This tool provides descriptions of many of these efforts that have been undertaken within recent decades, including some work from the 1960s that is still relevant. It provides a catalog of approaches that are useful for meeting current and future analytic needs. Links to reports on projects using these models and to technical literature regarding the methods used are provided to assist researchers seeking to adapt these modeling approaches to their own use.

Most of the models described in this tool are *inventory projection models* that depict changes in personnel inventories over future periods. They vary in terms of the dimensions of the inventories depicted in the models (grade, years of service, etc.) and the methods used to predict future inventories. Other types of models described in this tool include retention models, a recruiting resource model, a disparate impact model, and various manpower requirements models. The final chapters provide sources and methodologies for incorporating costs into inventory models and advice on choosing a modeling approach.

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Chapter 1

Introduction

Personnel modeling at RAND began in the 1960s, with the earliest documentation being a 1960 report entitled *An Application of a Network Flow Model to Personnel Planning* (Gorham, 1960). This and subsequent efforts were based on the insight that personnel inventories behaved similarly to logistics inventories and could be analyzed by applying the operations research methodologies that are commonly used in logistics management. As personnel modeling progressed, refinements drawn from statistics, econometrics, industrial and organizational psychology, and other fields of study enriched the genre. More recently, artificial intelligence applications have begun to influence model development.

A survey of the personnel inventory modeling literature reveals that there is a large representation of work by RAND and other organizations that focuses on military personnel management. This can be attributed to the centralized management of military personnel inventories. In contrast, most nonmilitary organizations tend to decentralize their personnel management decisions to form larger numbers of smaller workforce pools for which model-based decisionmaking is less advantageous.

As personnel inventory modeling became more prevalent, the field itself became a focus of study. In a 1973 study, the Naval Personnel Research and Development Laboratory, in cooperation with the Air Force Military Personnel Center, created a compendium of extant personnel modeling efforts within the military services. The study team found 101 Navy models and 130 non-Navy models that they classified by model type and the techniques employed. Figures 1.1 and 1.2 show the team's results. Of particular interest is the team's taxonomy of modeling techniques.

Figure 1.1. Navy Models in the 1973 Compendium

NAVY MODELS

COMPUTER MODEL CLASSIFICATIONS VERSUS TECHNIQUES EMPLOYED								
MODEL CLASSIFICATIONS	TECHNIQUES EMPLOYED							
	STOCHASTIC			DETERMINISTIC				
	SYSTEM SIMULATION		GAMING	ANALYTIC (Mathematical)	ANALYTIC (Statistical)	MATHEMATICAL PROGRAMMING	GAME THEORETIC	TOTAL
	BULK-FLOW	ENTITY						
Determination of Manpower Requirements Models CATEGORY I	1	9		9		4		23
Active Inventory Maintenance Models CATEGORY II		1		9	4	6		20
Inventory Projection Models CATEGORY III	2	7		4	5	1		19
Requirements/Inventory Analysis and Projection Models CATEGORY IV				8	1	4		13
Policy Alternative Generator Models CATEGORY V	1			2	3	5		11
Productivity Measurement Models CATEGORY VI		8		4		3		15
TOTAL	4	25		36	13	23		101

SOURCE: Reproduced from Hutchins et al., 1973, p. 82.

Figure 1.2. Non-Navy Models in the 1973 Compendium

NON-NAVY MODELS

COMPUTER MODEL CLASSIFICATIONS VERSUS TECHNIQUES EMPLOYED

MODEL CLASSIFICATIONS	TECHNIQUES EMPLOYED							TOTAL
	STOCHASTIC			DETERMINISTIC				
	SYSTEM SIMULATION		GAMING	ANALYTIC (Mathematical)	ANALYTIC (Statistical)	MATHEMATICAL PROGRAMMING	GAME THEORETIC	
	BULK-FLOW	ENTITY						
Determination of Manpower Requirements Models CATEGORY I	3	7	1	11	6	3	1	32
Active Inventory Maintenance Models CATEGORY II	4	3		3	7	4		21
Inventory Projection Models CATEGORY III	7	14		6	1	1	1	30
Requirements/Inventory Analysis and Projection Models CATEGORY IV	1	4		3	2	3		13
Policy Alternative Generator Models CATEGORY V	4	10	1	4	1	4		24
Productivity Measurement Models CATEGORY VI		6		3			1	10
TOTAL	19	44	2	30	17	15	3	130

SOURCE: Reproduced from Hutchins et al., 1973, p. 83.

In 1982, RAND researchers Carter, Chaiken, and Walker surveyed the enlisted force management systems of the four defense services in preparation for work on an Enlisted Force Management System for the Air Force, which later emerged as a constellation of linked models. They

identified these systems to be supported by modeling efforts, similar to the model classifications found in the Naval Personnel Research and Development Laboratory analysis:

- Requirements Determination
- Authorization Management
- Personnel Planning
- Personnel Programming
- Personnel Requisition and Assignment
- Support for [Planning Programming, Budgeting, and Execution System] Cycle
- Other Reporting
- Total Force Planning and Mobilization Management. (Hutchins et al., 1973)

At the beginning of an analysis, contemporary modelers continue to debate where to place their models within the Navy study's taxonomy, particularly within the stochastic versus deterministic and bulk-flow versus entity dichotomies that are reflected in the techniques-employed dimension. In this context, a *stochastic* (or Monte Carlo) model incorporates a probabilistic random draw regarding one or more state-change parameters, such as the continuation rate at which individuals survive from one period to the next in an inventory model. To account for the range of probable outcomes, the model is run multiple times (hundreds or thousands of iterations).[1] Stochastic models can generally provide probability distributions of the outcomes, which help to define the policy space. In contrast, *deterministic* models are run with a single iteration to produce point estimates of each outcome. Entity models will almost always be stochastic to avoid random outlier outcomes, which could occur if run deterministically. However, bulk-flow models can be and generally are deterministic.[2]

Contemporary personnel modeling at RAND is conducted primarily within four programs: Project AIR FORCE's Workforce, Development, and Health Program; the Arroyo Center's Personnel, Training, and Health Program; the National Security Research Division's Personnel, Readiness, and Health Program; and the Homeland Security Research Division's Management, Technology, and Capabilities Program. This tool provides a sampling of modeling efforts, which are conducted within these programs, with the objective of helping researchers visualize useful approaches to the analytic challenges they face.

Organization of the Tool

The ensuing chapters each present one or more examples of a type of model. In some cases, this tool reproduces illustrative figures and tables drawn from the original publications that document these models. For statistical significance and other details of research findings, readers should consult the original publications.

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[1] The context in which the term *stochastic* is being used here is narrower than the general use of the term. Typically, models that use distributions of random variables and incorporate uncertainty (variance) into estimation are considered stochastic whether or not repeated runs are employed. Thus, statistical models are generally considered to be stochastic models, which is contrary to this narrower classification reflected in Figures 1.1 and 1.2.

[2] The Naval Personnel Research and Development Laboratory analysis does not seem to recognize the validity of deterministic system-simulation models, but they are, in fact, common.

- Chapter 2 describes a Markovian inventory projection model that was developed for use with civilian workforces. It is the simplest model described in this tool and is easily implemented in a Microsoft Excel workbook.
- Chapter 3 describes the Compensation, Accessions, and Personnel Management (CAPM) model, which is an older model named after the three major directorates within the Office of the Deputy Assistant Secretary of Defense for Military Personnel Policy whose policy analytic needs the model was intended to serve. It is unique because it incorporated both then state-of-the-art compensation and retention modeling and inventory projection modeling in the same instrument.
- Chapter 4 describes the Total Force Blue Line (TFBL) model, which introduces an unusual use—and perhaps the first use—of an optimization (linear programming) approach to align personnel inventory projections with requirements.
- Chapter 5 describes an optimization model fashioned after the TFBL model, but which has the addition of a grade dimension to permit exploration of promotion-related phenomena. It illustrates the challenge of incorporating grades and promotions in inventory projection models.
- Chapter 6 describes an entity-level General Officer Flow Model intended to assist in senior leader promotion planning.
- The CAPM model, presented in Chapter 3, features the use of the annualized cost of leaving (ACOL) methodology, which is an early econometric approach for relating compensation to retention. In Chapter 7, the contemporary evolution of that approach—the Dynamic Retention Model—is discussed.
- Chapter 8 presents a comparison between parametric statistical (e.g., regression) and algorithmic (machine learning, nonparametric) approaches to modeling relationships among variables, both in the context of miliary service retention.
- In Chapter 9, we focus on modeling the relationship between input resources and personnel outcomes, specifically for military recruiting.
- Chapter 10 describes a state-of-the-art model used to test for disparate impacts in personnel management outcomes.
- In Chapter 11, we turn from supply-side to demand-side modeling efforts.
- Chapter 12 highlights efforts to fully account for workforce costs.
- Chapter 13 provides a summary of modeling considerations.

Chapter 2

A Simple Inventory Projection Model

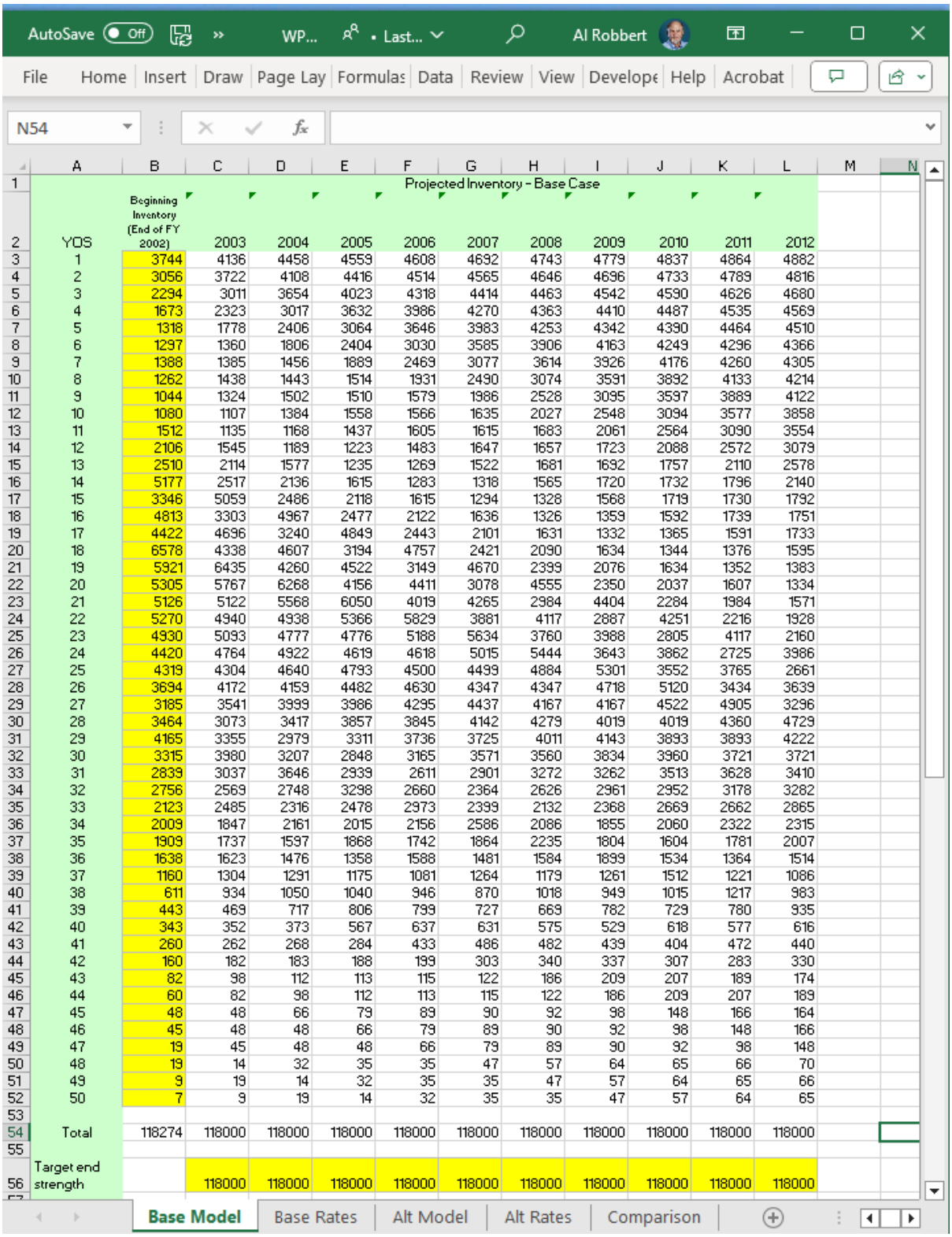
The term *inventory projection model* was commonly used by late 20th century planners and programmers in the U.S. Department of Defense (DoD) to characterize analytic tools that were built for exploring expected or alternative accession, retention, cost, and other impacts on personnel management policies inventories by simulating changes in the inventories as they age through future periods. The earliest examples were typically bulk-flow models in which the inventory cells were defined by a years-of-service (YOS) dimension, perhaps within some larger aggregation, such as military occupational specialty. The models typically projected five or more years into the future in one-year increments, starting from an observed *beginning inventory*—the baseline inventory of personnel as reflected in personnel data. A state-change parameter—a *continuation rate*—was used to age the inventory from one projected year to the next. This rate was the proportion of the inventory in YOS y at time t that survived to YOS $y + 1$ at time $t + 1$. The continuation rate was easily derived from historic inventory records by observing snapshots of the population in two or more successive years. The only additional parameters needed for a minimally dimensioned model were the projected total sizes of the inventory at the end of each future year. YOS 1 (the inventory with less than a year of service)[3] in projected periods was equal to the total inventory planned or anticipated for a projected period minus the total of the projected inventory surviving from the previous period.[4]

Figure 2.1 depicts a worksheet from a simple Excel-based inventory projection model developed for the DoD acquisition workforce (Gates et al., 2008). Other worksheets in the model are indicated by the row of tabs at the bottom of the figure. Of note is the *base rates* tab, shown in Figure 2.2, which contains the continuation rates used in the model. Column A contains the loss rates observed during the year prior to the modeling period, and the remaining columns convert the loss rates to continuation rates by subtracting from one. The rates are identical for each projected year of the model but could be varied from year to year, as discussed below.

[3] Some modelers may use YOS 0 to designate the first year of service.

[4] More-elaborate forms of such models would also account for losses within the first year of service and, perhaps, place constraints on the number of gains in projected periods.

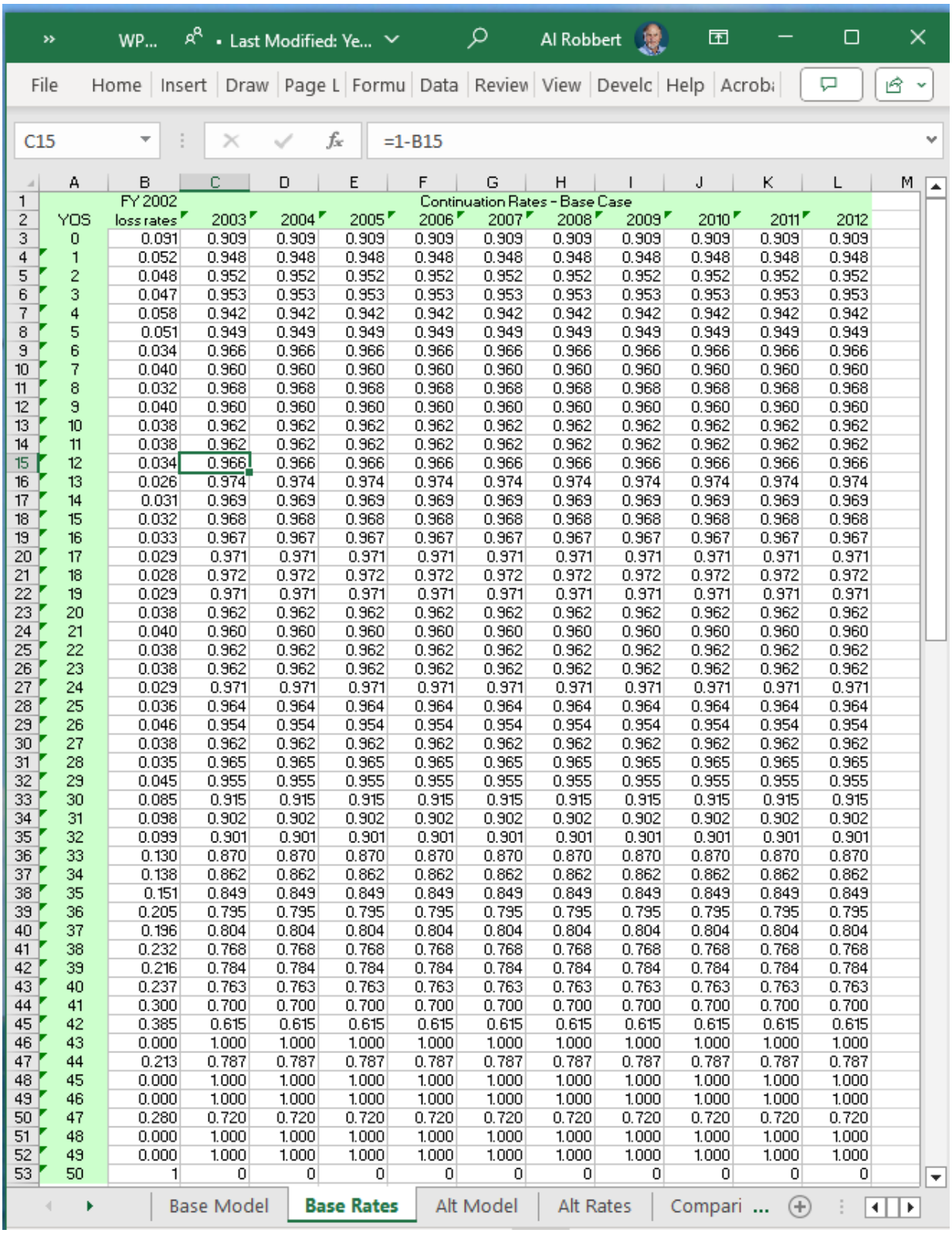
Figure 2.1. Simple Inventory Projection Model—Inventory Display



	A	B	C	D	E	F	G	H	I	J	K	L
1			Projected Inventory - Base Case									
2	YOS	Beginning Inventory (End of FY 2002)	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
3	1	3744	4136	4458	4559	4608	4692	4743	4779	4837	4864	4882
4	2	3056	3722	4108	4416	4514	4565	4646	4696	4733	4789	4816
5	3	2294	3011	3654	4023	4318	4414	4463	4542	4590	4626	4680
6	4	1673	2323	3017	3632	3986	4270	4363	4410	4487	4535	4569
7	5	1318	1778	2406	3064	3646	3983	4253	4342	4390	4464	4510
8	6	1297	1360	1806	2404	3030	3585	3906	4163	4249	4296	4366
9	7	1388	1385	1456	1889	2469	3077	3614	3926	4176	4260	4305
10	8	1262	1438	1443	1514	1931	2490	3074	3591	3892	4133	4214
11	9	1044	1324	1502	1510	1579	1986	2528	3095	3597	3889	4122
12	10	1080	1107	1384	1558	1566	1635	2027	2548	3094	3577	3858
13	11	1512	1135	1168	1437	1605	1615	1683	2061	2564	3090	3554
14	12	2106	1545	1189	1223	1483	1647	1657	1723	2088	2572	3079
15	13	2510	2114	1577	1235	1269	1522	1681	1692	1757	2110	2578
16	14	5177	2517	2136	1615	1283	1318	1565	1720	1732	1796	2140
17	15	3346	5059	2486	2118	1615	1294	1328	1568	1719	1730	1792
18	16	4813	3303	4967	2477	2122	1636	1326	1359	1592	1739	1751
19	17	4422	4696	3240	4849	2443	2101	1631	1332	1365	1591	1733
20	18	6578	4338	4607	3194	4757	2421	2090	1634	1344	1376	1595
21	19	5921	6435	4260	4522	3149	4670	2399	2076	1634	1352	1383
22	20	5305	5767	6268	4156	4411	3078	4555	2350	2037	1607	1334
23	21	5126	5122	5568	6050	4019	4265	2984	4404	2284	1984	1571
24	22	5270	4940	4938	5366	5829	3881	4117	2887	4251	2216	1928
25	23	4930	5093	4777	4776	5188	5634	3760	3988	2805	4117	2160
26	24	4420	4764	4922	4619	4618	5015	5444	3643	3862	2725	3986
27	25	4319	4304	4640	4793	4500	4499	4884	5301	3552	3765	2661
28	26	3694	4172	4159	4482	4630	4347	4347	4718	5120	3434	3639
29	27	3185	3541	3999	3986	4295	4437	4167	4167	4522	4905	3296
30	28	3464	3073	3417	3857	3845	4142	4279	4019	4019	4360	4729
31	29	4165	3355	2979	3311	3736	3725	4011	4143	3893	3893	4222
32	30	3315	3980	3207	2848	3165	3571	3560	3834	3960	3721	3721
33	31	2839	3037	3646	2939	2611	2901	3272	3262	3513	3628	3410
34	32	2756	2569	2748	3298	2660	2364	2626	2961	2952	3178	3282
35	33	2123	2485	2316	2478	2973	2399	2132	2368	2669	2662	2865
36	34	2009	1847	2161	2015	2156	2586	2086	1855	2060	2322	2315
37	35	1909	1737	1597	1868	1742	1864	2235	1804	1604	1781	2007
38	36	1638	1623	1476	1358	1588	1481	1584	1899	1534	1364	1514
39	37	1160	1304	1291	1175	1081	1264	1179	1261	1512	1221	1086
40	38	611	934	1050	1040	946	870	1018	949	1015	1217	983
41	39	443	469	717	806	799	727	669	782	729	780	935
42	40	343	352	373	567	637	631	575	529	618	577	616
43	41	260	262	268	284	433	486	482	439	404	472	440
44	42	160	182	183	188	199	303	340	337	307	283	330
45	43	82	98	112	113	115	122	186	209	207	189	174
46	44	60	82	98	112	113	115	122	186	209	207	189
47	45	48	48	66	79	89	90	92	98	148	166	164
48	46	45	48	48	66	79	89	90	92	98	148	166
49	47	19	45	48	48	66	79	89	90	92	98	148
50	48	19	14	32	35	35	47	57	64	65	66	70
51	49	9	19	14	32	35	35	47	57	64	65	66
52	50	7	9	19	14	32	35	35	47	57	64	65
53												
54	Total	118274	118000	118000	118000	118000	118000	118000	118000	118000	118000	118000
55												
56	Target end strength		118000	118000	118000	118000	118000	118000	118000	118000	118000	118000

SOURCE: Reproduced from an unpublished application developed by the primary author (Robbert) in 2001.

Figure 2.2. Simple Inventory Projection Model—Continuation Rates Matrix



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C15 =1-B15

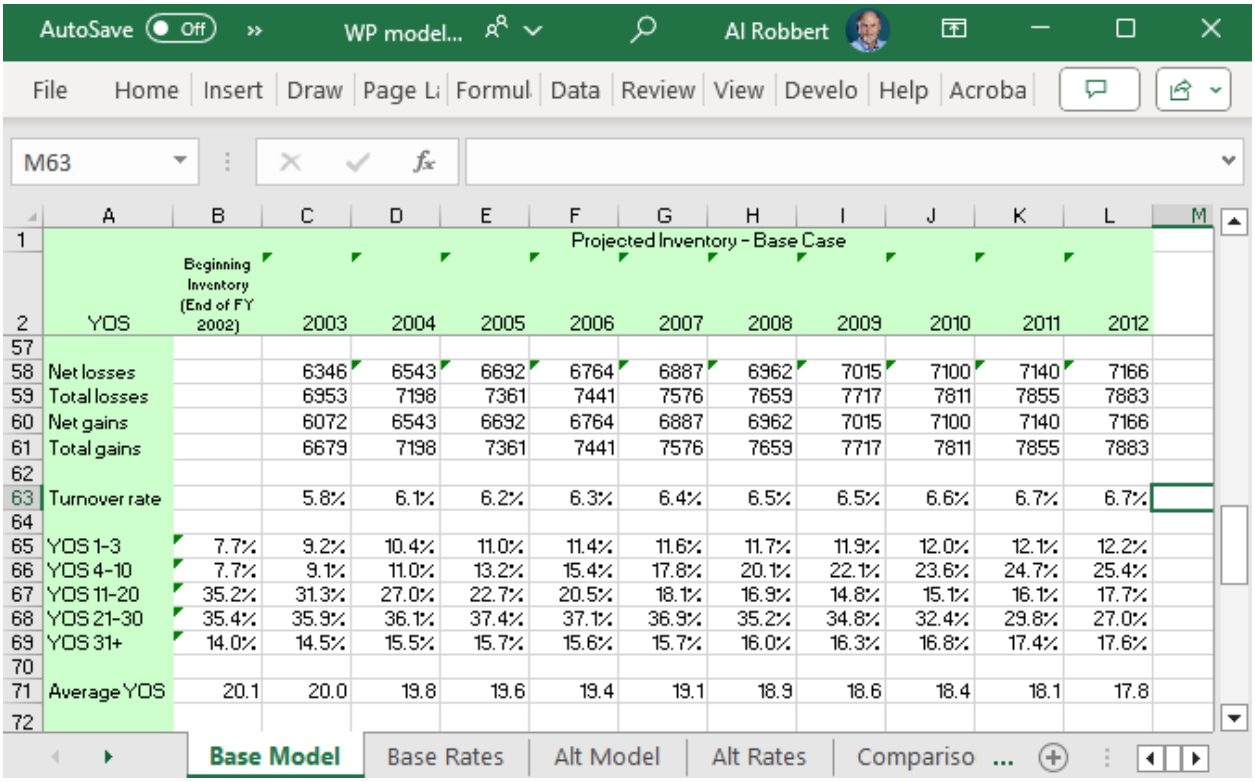
	A	B	C	D	E	F	G	H	I	J	K	L	M
1		FY 2002	Continuation Rates - Base Case										
2	YOS	loss rates	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	
3	0	0.091	0.909	0.909	0.909	0.909	0.909	0.909	0.909	0.909	0.909	0.909	
4	1	0.052	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948	0.948	
5	2	0.048	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	0.952	
6	3	0.047	0.953	0.953	0.953	0.953	0.953	0.953	0.953	0.953	0.953	0.953	
7	4	0.058	0.942	0.942	0.942	0.942	0.942	0.942	0.942	0.942	0.942	0.942	
8	5	0.051	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	
9	6	0.034	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	
10	7	0.040	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	
11	8	0.032	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	
12	9	0.040	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	
13	10	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
14	11	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
15	12	0.034	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	0.966	
16	13	0.026	0.974	0.974	0.974	0.974	0.974	0.974	0.974	0.974	0.974	0.974	
17	14	0.031	0.969	0.969	0.969	0.969	0.969	0.969	0.969	0.969	0.969	0.969	
18	15	0.032	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	0.968	
19	16	0.033	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	0.967	
20	17	0.029	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	
21	18	0.028	0.972	0.972	0.972	0.972	0.972	0.972	0.972	0.972	0.972	0.972	
22	19	0.029	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	
23	20	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
24	21	0.040	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	0.960	
25	22	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
26	23	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
27	24	0.029	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	0.971	
28	25	0.036	0.964	0.964	0.964	0.964	0.964	0.964	0.964	0.964	0.964	0.964	
29	26	0.046	0.954	0.954	0.954	0.954	0.954	0.954	0.954	0.954	0.954	0.954	
30	27	0.038	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962	
31	28	0.035	0.965	0.965	0.965	0.965	0.965	0.965	0.965	0.965	0.965	0.965	
32	29	0.045	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	0.955	
33	30	0.085	0.915	0.915	0.915	0.915	0.915	0.915	0.915	0.915	0.915	0.915	
34	31	0.098	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.902	
35	32	0.099	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	0.901	
36	33	0.130	0.870	0.870	0.870	0.870	0.870	0.870	0.870	0.870	0.870	0.870	
37	34	0.138	0.862	0.862	0.862	0.862	0.862	0.862	0.862	0.862	0.862	0.862	
38	35	0.151	0.849	0.849	0.849	0.849	0.849	0.849	0.849	0.849	0.849	0.849	
39	36	0.205	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	
40	37	0.196	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	0.804	
41	38	0.232	0.768	0.768	0.768	0.768	0.768	0.768	0.768	0.768	0.768	0.768	
42	39	0.216	0.784	0.784	0.784	0.784	0.784	0.784	0.784	0.784	0.784	0.784	
43	40	0.237	0.763	0.763	0.763	0.763	0.763	0.763	0.763	0.763	0.763	0.763	
44	41	0.300	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	0.700	
45	42	0.385	0.615	0.615	0.615	0.615	0.615	0.615	0.615	0.615	0.615	0.615	
46	43	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
47	44	0.213	0.787	0.787	0.787	0.787	0.787	0.787	0.787	0.787	0.787	0.787	
48	45	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
49	46	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
50	47	0.280	0.720	0.720	0.720	0.720	0.720	0.720	0.720	0.720	0.720	0.720	
51	48	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
52	49	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
53	50	1	0	0	0	0	0	0	0	0	0	0	

Base Model | Base Rates | Alt Model | Alt Rates | Compari ...

SOURCE: Reproduced from an unpublished application developed by the primary author (Robbert) in 2001.

This model was originally constructed in response to concerns, particularly within the DoD acquisition community, that a large proportion of the acquisition workforce was or soon would be eligible for retirement. The fear was that a mass exodus of experienced workers would occur. Note that continuation rates are generally above 95 percent through the first 29 YOS, which indicates very limited turnover prior to retirement eligibility. Even after retirement eligibility, continuation rates generally remain above 75 percent, which confirms that a workforce with a high proportion of retirement eligibles would experience increased losses but not a mass exodus. The policy-relevant finding was that the turnover rate, as indicated in Figure 2.3, would remain within manageable bounds without the need for extraordinary retention measures.

Figure 2.3. Inventory Projection Model—Analytic Results



	A	B	C	D	E	F	G	H	I	J	K	L
1			Projected Inventory - Base Case									
2	YOS	Beginning Inventory (End of FY 2002)	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
57												
58	Net losses		6346	6543	6692	6764	6887	6962	7015	7100	7140	7166
59	Total losses		6953	7198	7361	7441	7576	7659	7717	7811	7855	7883
60	Net gains		6072	6543	6692	6764	6887	6962	7015	7100	7140	7166
61	Total gains		6679	7198	7361	7441	7576	7659	7717	7811	7855	7883
62												
63	Turnover rate		5.8%	6.1%	6.2%	6.3%	6.4%	6.5%	6.5%	6.6%	6.7%	6.7%
64												
65	YOS 1-3	7.7%	9.2%	10.4%	11.0%	11.4%	11.6%	11.7%	11.9%	12.0%	12.1%	12.2%
66	YOS 4-10	7.7%	9.1%	11.0%	13.2%	15.4%	17.8%	20.1%	22.1%	23.6%	24.7%	25.4%
67	YOS 11-20	35.2%	31.3%	27.0%	22.7%	20.5%	18.1%	16.9%	14.8%	15.1%	16.1%	17.7%
68	YOS 21-30	35.4%	35.9%	36.1%	37.4%	37.1%	36.9%	35.2%	34.8%	32.4%	29.8%	27.0%
69	YOS 31+	14.0%	14.5%	15.5%	15.7%	15.6%	15.7%	16.0%	16.3%	16.8%	17.4%	17.6%
70												
71	Average YOS	20.1	20.0	19.8	19.6	19.4	19.1	18.9	18.6	18.4	18.1	17.8
72												

SOURCE: Reproduced from an unpublished application developed by the primary author (Robbert) in 2001.
NOTE: The difference between net and total losses and gains is the number of losses occurring within the first year of service.

More-sophisticated versions of models such as the depicted inventory projection model might use continuation rates that depart from historically observed values as a function of some exogenous or policy variables. However, lacking an analytically derived function for determining alternative continuation rates, an analyst willing to make reasonable assumptions about the behavioral effects of exogenous or policy variables could intuitively vary the continuation rates and observe the impacts on future inventories.

More-elaborate versions of inventory projection models would incorporate additional dimensions. As mentioned above, occupational groups can be introduced as a dimension relatively easily, introducing the need for a state-change parameter reflecting lateral movement among groups—which is a relatively simple elaboration. Introducing grade as a dimension is more difficult because it requires determining a total promotion requirement for each grade (analogous to determining the overall YOS 1 population in each projected year) and YOS distributions of the expected numbers of annual promotions to each grade. The latter becomes problematic if the YOS distribution of the inventory does not remain stable throughout the projected periods. Demographic differences that are relevant for cost, behavior, or policy purposes can also be incorporated, with attendant complexities in determining and applying state-change rates.

Chapter 3

The Compensation, Accessions, and Personnel Management Model

The CAPM model is an example of a full-featured inventory projection model. It was constructed and maintained by RAND during the period from 1991 through 1994 for use by the Compensation Directorate of the Office of the Secretary of Defense (OSD). It was later adopted for use by the Air Force, which, jointly with OSD, sponsored maintenance of the model from 1999 to 2001 (Ausink, Cave, and Carrillo, 2003; Ausink et al., 2003).

The inventories projected in the model were the enlisted forces of any of the military services. Inventories were carried at grade and YOS dimensions.

A version of the model can be downloaded by following the link provided in the bibliographic entry for Ausink et al. (2003, p. 6). We were unable to open and exercise the model, possibly because of incompatibility with the older macro coding and the current version of Excel. Interested users with more persistence might be more successful.

A core feature of the model was that it developed continuation rates dynamically as a function of expected compensation attributed to populations represented in the model. With grade as a dimension and compensation dependent on grade, the model required a complex interaction of promotion and retention computations. To predict retention, the model used a version of the ACOL model. Ausink, Cave, and Carrillo (2003, p. 6) provides this description of the ACOL model:

> In this model developed by Warner (1979) for a study of retention in the enlisted force, the utility of a decision is simply the present value of the income stream from that decision, and an individual is assumed to be capable of surveying the future to determine income streams from different sources. Each individual is also assumed to have a certain "taste" for the military that is expressed as the equivalent of γ dollars that are added to current income. If an individual leaves now, he or she will receive wages from the new job from now until mandatory retirement from that job. If an individual chooses to wait until a future year r to leave for a new job, he or she will receive military wages (plus the added value of the "taste" for the military) each year until year $r - 1$ and wages from the new job from year r until mandatory retirement from the new job.

The model assumes that individuals will behave (stay or leave) at each decision point in a way that minimizes their expected cost of leaving. Thus, the name of the model.

Ausink, Cave, and Carrillo (2003) also discusses the ACOL 2 model (the version used in the CAPM model), which better differentiates between the effects of individual specific tastes and additional random shocks, and the Dynamic Retention Model (DRM), which incorporates a more complex structure for individuals' simulated estimates of the future utility of various career paths

(Gotz and McCall, 1984; Mattock and Asch, 2023). The DRM was considered too complex for implementation in the CAPM model.

Chapter 4

The Total Force Blue Line Model

The TFBL model was constructed to predict the future rated inventories of the Regular Air Force (RegAF), Air Force Reserve (AFR), and Air National Guard (ANG) and accounts for expected interactions among them (Terry et al., 2019).[5] The Air Force considers its rated inventory to be its most essential personnel resource. It perennially struggles to develop inventories large enough to meet requirements, investing heavily in both pipeline training and retention incentives. The policies that guide these investments are predicated on comparisons of inventory forecasts and requirements. The TFBL model was built to improve on earlier, less sophisticated inventory forecasts.

As with most inventory projection models, the TFBL model depends on exogenously derived loss or continuation rates. The modelers derived loss rates from several sources, including an adjustment for expected airline hiring developed in McGee (2015).

The model is unique among contemporary inventory models because it is implemented as an optimization (linear programming) model.[6] An optimization model seeks to maximize or minimize some function, subject to a series of constraints. The TFBL model was thus characterized by its creators as follows:

> The objective of the [TFBL] model is to adopt a forward-looking perspective to identify the number of personnel to assign to requirements within a category., where a requirement is defined by a [rated category] (e.g., pilot, [combat systems officer], [air battle manager], [remotely piloted aircraft] pilot), a component (RegAF, AFR, or ANG); and a [major weapon system] or [an air force specialty] (e.g., bomber, fighter 11M, etc.). The model finds the best solution such that the number of unfilled requirements is minimized and the number of officers assigned to a requirement category is maximized while producing the fewest number of officers possible. (Terry and Kilambi, 2023, p. 6)

The model was originally implemented in SAS but has since been rewritten in Python with a web application or Jupyter Notebook as a user interface (Terry and Kilambi, 2023, p. 12).[7] The SAS or Python code for an optimization model establishes the framework for finding a solution but does not actually compute the solution. Rather, it invokes one of several available solvers to find a solution. The solver iteratively varies the values of the variables in the model using an algorithm that systematically seeks optimal levels, as defined by the model's objective function.

[5] The term *rated* applies to officers who possess an aeronautical rating. The model derives its name from the conventional graphic projection of rated requirements and inventory over future fiscal years (FYs). The requirements are conventionally depicted using a red line, while inventories are depicted using a blue line—hence, the name of the model used to generate the blue line data.

[6] For an example of an earlier inventory model built upon an optimization framework, see Bateman, 1994.

[7] A Jupyter Notebook is a web-based interactive development environment for notebooks, code, and data. See Jupyter, undated.

Technical Model Formulation

The key elements of the model are its variables, objective function, and constraints. The full specification of these and other elements (scalars, index sets, parameters, boundary conditions) can be found in Terry et al. (2019, pp. 54–64). Selected elements are described below. Variables included in these descriptions have multiple dimensions (e.g., rated category, component, commissioned year of service, weapon system). For simplicity, the dimensionality of the variables is not shown.

Objective Function

The objective function specifies that the model minimizes the sum of the following variables:

- unassigned inventory
- unfilled requirements
- pilot production
- positive deviations from historic affiliation rates[8]
- negative deviations from historic affiliation rates.

Constraints

The key constraints (somewhat simplified) are the following:

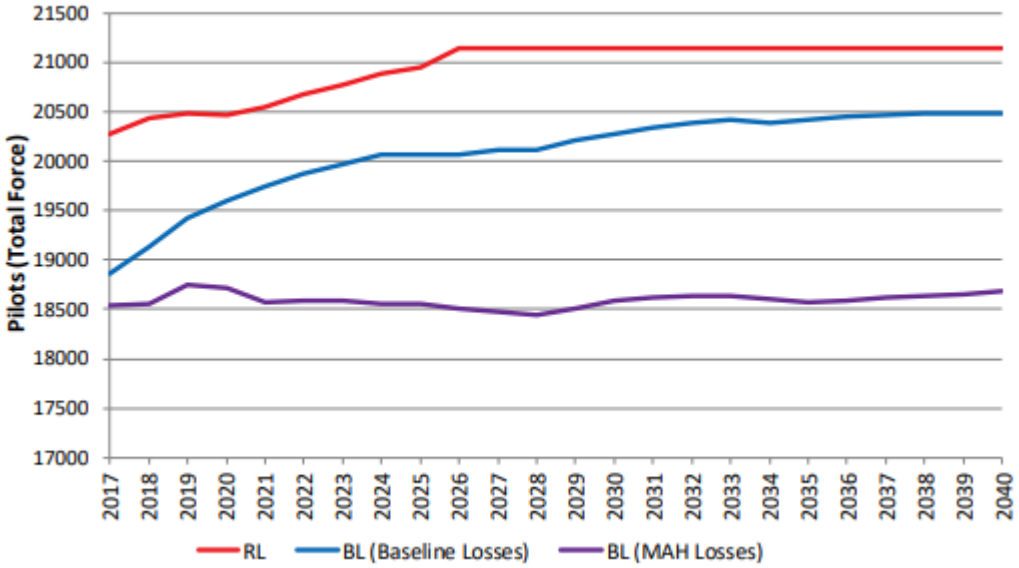
- Unfilled requirements plus filled requirements (assigned personnel) equal total requirements.
- Assigned personnel plus unassigned personnel equal total inventory.
- Inventory in a period is equal to the inventory at the end of the previous period plus gains in the period minus losses in the period.
- Separations in a period are equal to the inventory at the end of the previous period multiplied by the loss rate in that period.
- Total gains are equal to the proportional distribution of produced officers by rated category multiplied by total production plus total affiliations.
- Affiliations plus unaffiliated separations equal total separations from the RegAF.

Typical Output

Figure 4.1 depicts a red-line stream of requirements and two blue-line inventory projections (one of which is purple to differentiate it from the other). One of the inventory projections (the blue line) is based on RegAF losses unadjusted for expected airline hiring. The other (the purple line) is based on losses calculated according to McGee (2015) to account for expected airline hiring.

[8] An *affiliation rate* indicates the proportion of officers separating from the RegAF who subsequently affiliate in a rated capacity with the AFR or ANG.

Figure 4.1. A Red-Line/Blue-Line Graphic with Model-Generated Inventory Lines



SOURCE: Reproduced from Terry et al., 2019, p. 28.
NOTE: RL = red-line; BL = blue-line; MAH = Major Airline Hiring (scenario).

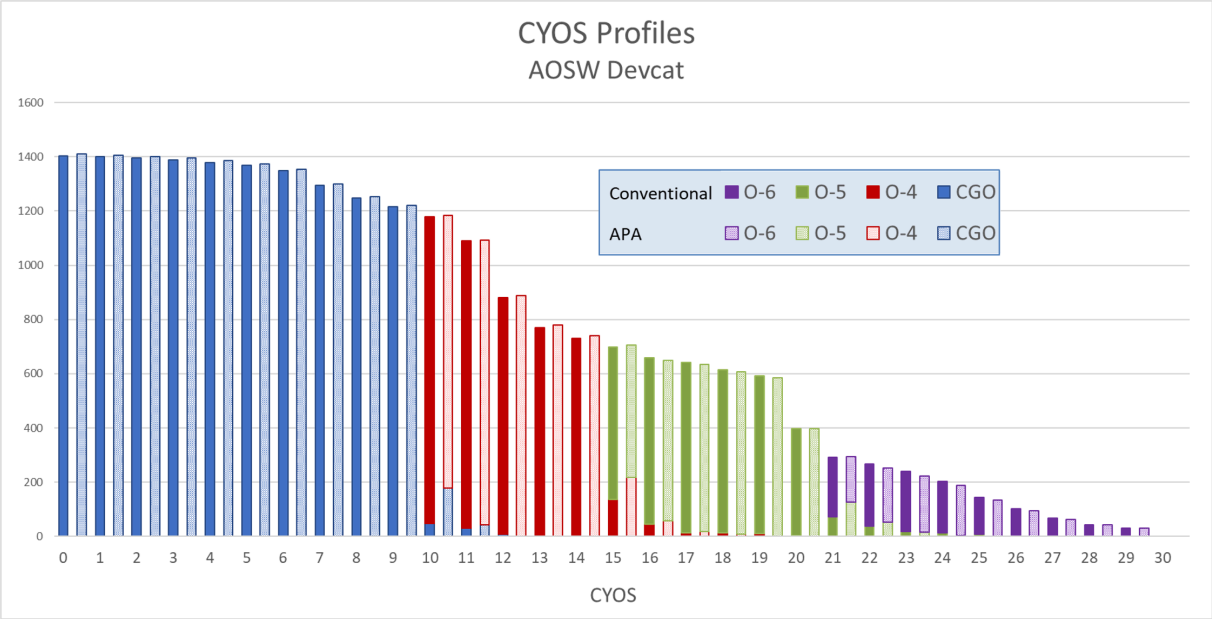
Chapter 5

An Optimizing Officer Promotion Model

Using the optimization approach to inventory modeling found in the TFBL model, Robbert et al. (2023) developed an optimization model to test the impacts of various promotion policies on field-grade officer inventories. Its primary purpose was to explore the impacts of adopting an *alternative promotion authority*, which is provided in Section 507 of the 2019 National Defense Authorization Act (Public Law 115-232, 2018). The authority can be found in U.S. Code, Title 10, Section 649. It provides military services the option to shift some or all officer promotion processes from the conventional framework with three promotion zones (below, in, and above the zone) to a single zone with multiple considerations. As of this writing, none of the services have shifted to the alternative authority.

By incorporating *grade* as a dimension of the inventories in the model (a necessity for analysis of promotion issues), this model added a degree of complexity not found in the TFBL model. The other inventory dimensions were *time in grade* (needed to determine part of the inventory that is within a promotion window) and *commissioned YOS* (used to determine losses from the inventory). Career field was not carried as a separate dimension in the model, but the inventories were disaggregated into developmental categories (broad groupings of career fields considered separately in promotion processes) and the model was run separately for each developmental category. Similar to the TFBL model, the model's objective is to minimize the inventory's deviations from grade requirements. It could be run in a steady-state mode (yielding the expected inventory if policies and parameters were held constant for an indefinite amount of time) or dynamic mode (projecting changing inventories over future periods). Among other outputs, the model provided contrasting YOS profiles under conventional and alternative promotion authorities, as illustrated in Figure 5.1.

Figure 5.1. Sample Steady-State Model Output



SOURCE: Reproduced from Robbert et al., 2023, p. 25.
NOTE: AOSW = Air Operations and Special Warfare; APA = alternative promotion authority; CGO = company-grade officer; CYOS = commissioned years of service. For these projections, promotion windows opened at year 10 for promotion to O-4, year 15 for promotion to O-5, and year 21 for promotion to O-6. Number of APA considerations were three for O-4 and five for O-5 and O-6. Promotion opportunities were consistent with the five-year promotion plan for the AOSW development category developed in 2020. Proportions of selections going to first-look eligible under APA were set at 85 percent and under the conventional promotion authority at the levels observed in 2020 boards (98 percent to O-4, 86 percent to O-5, and 90 percent to O-6).

Although this model was similar to the TFBL model in its approach, it differed in one important respect. The TFBL model was built as a linear programming model that is solvable with linear solvers. In the promotion model, an important policy constraint is the *promotion opportunity*—a prescribed proportion of eligible officers to be selected for promotion in an annual promotion cycle.[9] To ensure that modeled promotion selections adhere to this constraint, the model must determine selection rates by dividing one variable (the number of officers selected) by another variable (the number of officers eligible for promotion). Incorporating a constraint containing a nonlinear relationship (e.g., multiplication or division) between two variables requires the use of a nonlinear solver.[10] As was the case with this model, nonlinear solvers may fail to find feasible solutions, and the solutions that are found may be optimal locally rather than globally. Modelers can help the model avoid failure by adjusting starting values for key variables, but the nonlinear constraint required to capture this aspect of field-grade promotions presents a significant challenge.

[9] Some promotion opportunity constraints are set by law. U.S. Code, Title 10, Section 616, Subsection D limits the field-grade promotion opportunity to 95 percent. DoD policy (DoD Instruction 1320.13, 2021) also sets the desired ranges for promotion opportunity in field-grade promotions.

[10] Linear and nonlinear solvers differ in the algorithms used to converge on a solution.

Chapter 6

The General Officer Lifecycle Flow Model

The General Officer Lifecycle Flow (GOLF) model was built to assist the U.S. Air Force and the U.S. Space Force in managing their general officer promotion processes. It is used to

- project expected losses from the general officer inventory
- determine the number of general officers to be selected by future promotion boards
- determine the desired timing and frequency of future promotion boards.

GOLF is a stochastic entity model with entities representing officers differentiated by grade and date of rank. Simulated time in the model is continuous and asynchronous with event timing indicated by fractional years. Conventionally, the model is implemented in Excel with extensive Visual Basic customization. A basic version simulates retirements and promotions (the date a promotion is pinned on rather than the date of a promotion board) while a more advanced version also simulates promotion boards, promotion selections, and board membership. The more advanced version has also been implemented in Python.

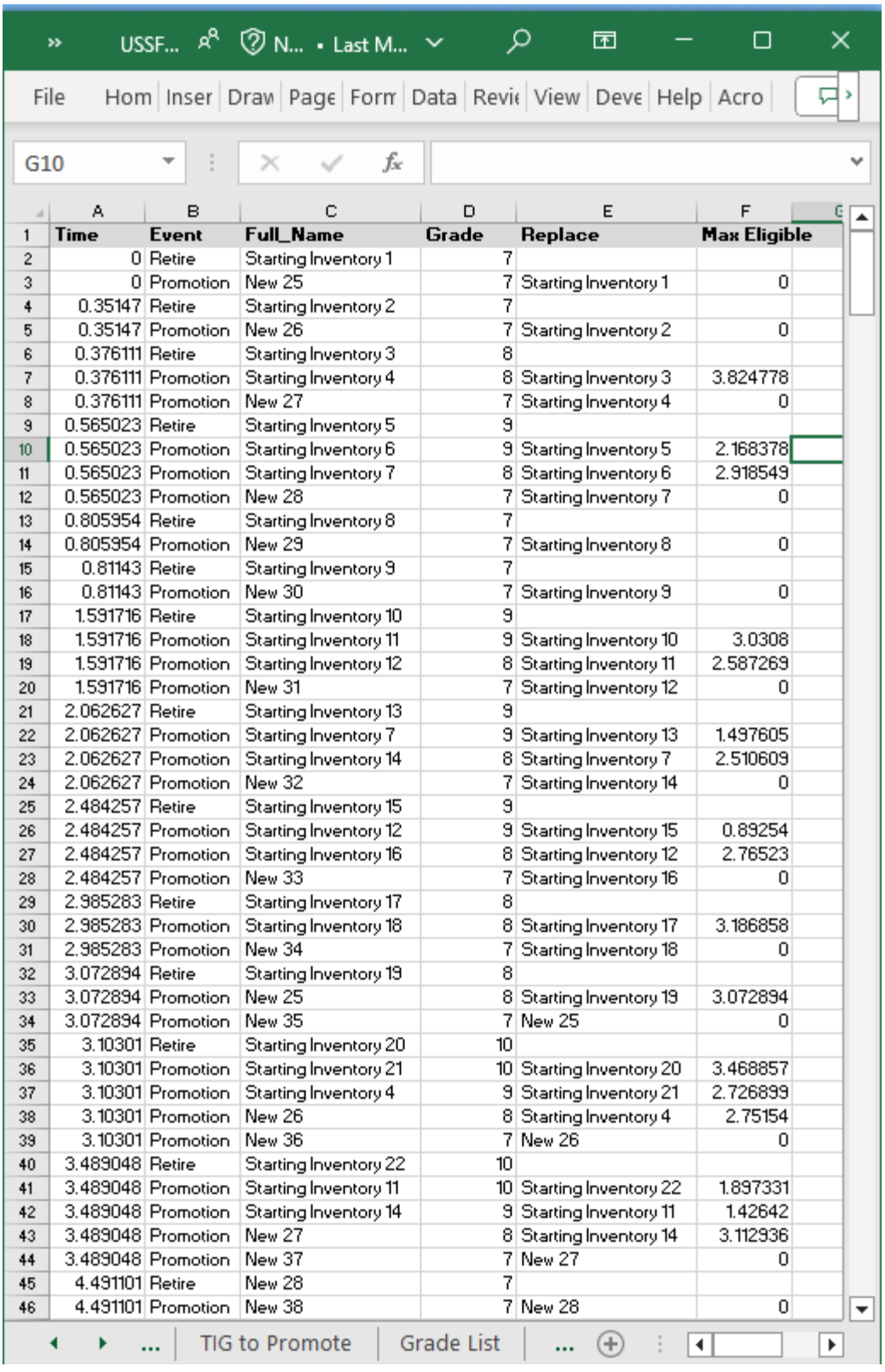
The basic version of the model is executed through the following multistep process:

- Each entity (i.e., representation of a specific officer) in the starting inventory is assigned a retirement date and a promotion date by adding random periods to its existing date of rank. The random periods are drawn from distributions, specific to a grade, which are derived from historical behavior.
- The model builds an event history with each event being a retirement of an entity reaching a retirement date, promotion of an entity to replace a retiring entity, or promotion of an entity to replace a promoted entity. Retirement of an entity in grade O-8 or above generates a daisy chain of promotions that ends with a promotion to grade O-7.
- For promotions to grade O-7, new entities are created.
- The entity selected for a promotion is the one whose randomly assigned promotion date most closely matches the simulation time of the precipitating retirement or promotion event.
- When an entity is promoted, a random draw from the time-to-retirement and time-to-promotion distributions is used to set new retirement and promotion dates.

Figure 6.1 shows the start of an event history from a run of the model used for the U.S. Space Force. In the *Full_Name* column, actual names as used in the model have been replaced with "Starting Inventory *x*" labels. New entities created by the model are labeled "New *x*" in the *Full_Name* column. For each promotion event, the *Max Eligible* column contains a calculation of the number of entities available for promotion at the simulated time, indicating the number of eligibles (a promotion

selectivity measure) available for the promotion. The model continues to a simulated time set by the user. After about ten years of simulated time, all entities in the starting inventory have retired, and all entities remaining in the inventory are those created by the model.

Figure 6.1. Portion of an Event History Table from the General Officer Lifecycle Flow Model (Basic Version)



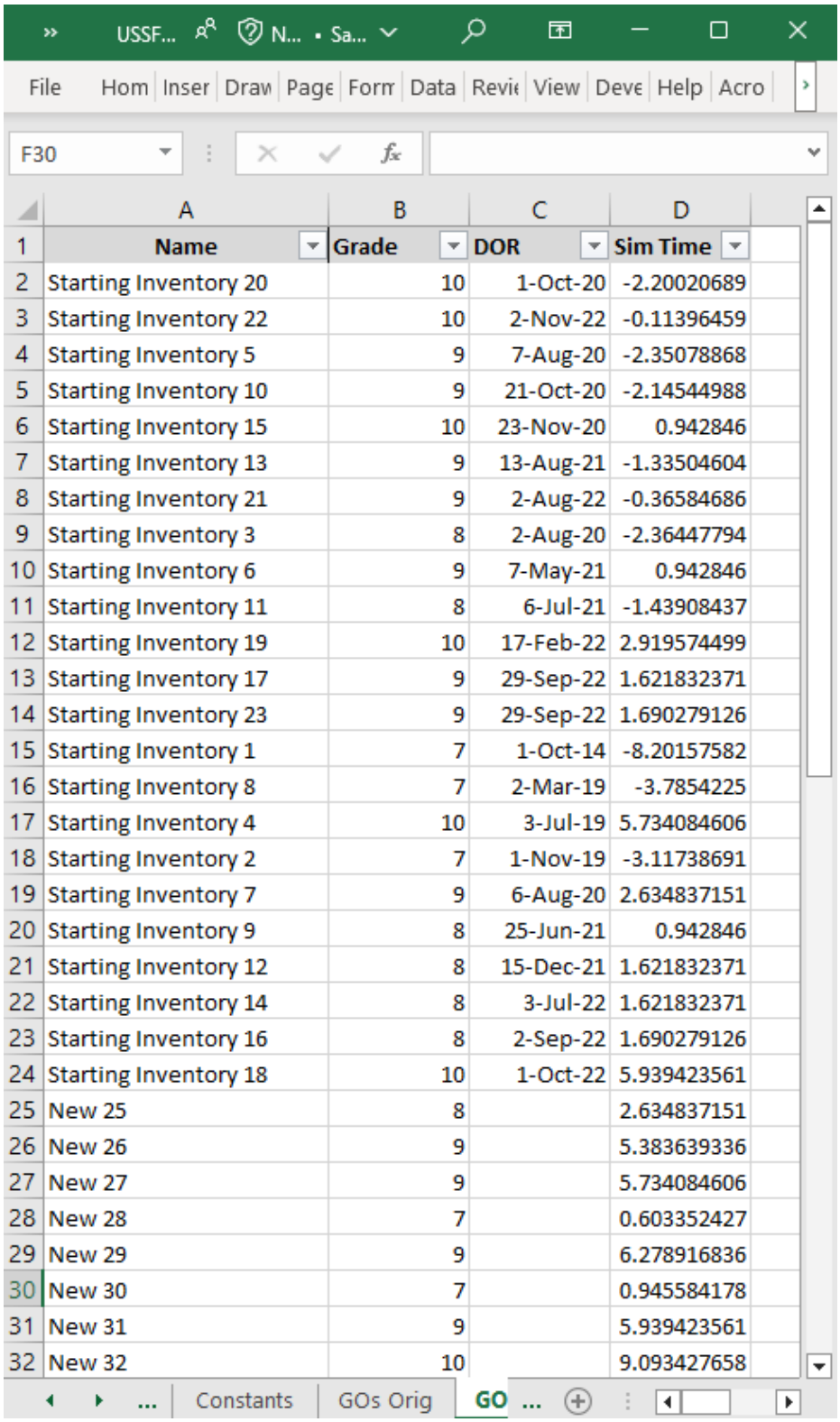
	A	B	C	D	E	F
1	Time	Event	Full_Name	Grade	Replace	Max Eligible
2	0	Retire	Starting Inventory 1	7		
3	0	Promotion	New 25	7	Starting Inventory 1	0
4	0.35147	Retire	Starting Inventory 2	7		
5	0.35147	Promotion	New 26	7	Starting Inventory 2	0
6	0.376111	Retire	Starting Inventory 3	8		
7	0.376111	Promotion	Starting Inventory 4	8	Starting Inventory 3	3.824778
8	0.376111	Promotion	New 27	7	Starting Inventory 4	0
9	0.565023	Retire	Starting Inventory 5	9		
10	0.565023	Promotion	Starting Inventory 6	9	Starting Inventory 5	2.168378
11	0.565023	Promotion	Starting Inventory 7	8	Starting Inventory 6	2.918549
12	0.565023	Promotion	New 28	7	Starting Inventory 7	0
13	0.805954	Retire	Starting Inventory 8	7		
14	0.805954	Promotion	New 29	7	Starting Inventory 8	0
15	0.81143	Retire	Starting Inventory 9	7		
16	0.81143	Promotion	New 30	7	Starting Inventory 9	0
17	1.531716	Retire	Starting Inventory 10	9		
18	1.531716	Promotion	Starting Inventory 11	9	Starting Inventory 10	3.0308
19	1.531716	Promotion	Starting Inventory 12	8	Starting Inventory 11	2.587269
20	1.531716	Promotion	New 31	7	Starting Inventory 12	0
21	2.062627	Retire	Starting Inventory 13	9		
22	2.062627	Promotion	Starting Inventory 7	9	Starting Inventory 13	1.497605
23	2.062627	Promotion	Starting Inventory 14	8	Starting Inventory 7	2.510609
24	2.062627	Promotion	New 32	7	Starting Inventory 14	0
25	2.484257	Retire	Starting Inventory 15	9		
26	2.484257	Promotion	Starting Inventory 12	9	Starting Inventory 15	0.89254
27	2.484257	Promotion	Starting Inventory 16	8	Starting Inventory 12	2.76523
28	2.484257	Promotion	New 33	7	Starting Inventory 16	0
29	2.985283	Retire	Starting Inventory 17	8		
30	2.985283	Promotion	Starting Inventory 18	8	Starting Inventory 17	3.186858
31	2.985283	Promotion	New 34	7	Starting Inventory 18	0
32	3.072894	Retire	Starting Inventory 19	8		
33	3.072894	Promotion	New 25	8	Starting Inventory 19	3.072894
34	3.072894	Promotion	New 35	7	New 25	0
35	3.10301	Retire	Starting Inventory 20	10		
36	3.10301	Promotion	Starting Inventory 21	10	Starting Inventory 20	3.468857
37	3.10301	Promotion	Starting Inventory 4	9	Starting Inventory 21	2.726899
38	3.10301	Promotion	New 26	8	Starting Inventory 4	2.75154
39	3.10301	Promotion	New 36	7	New 26	0
40	3.489048	Retire	Starting Inventory 22	10		
41	3.489048	Promotion	Starting Inventory 11	10	Starting Inventory 22	1.897331
42	3.489048	Promotion	Starting Inventory 14	9	Starting Inventory 11	1.42642
43	3.489048	Promotion	New 27	8	Starting Inventory 14	3.112936
44	3.489048	Promotion	New 37	7	New 27	0
45	4.491101	Retire	New 28	7		
46	4.491101	Promotion	New 38	7	New 28	0

Figure 6.2 shows the running inventory of general officers in the model. The starting inventory would be identified by actual names in the model, but, as with Figure 6.1, the actual names have been replaced by "Starting Inventory *x*" labels (numbered in the order in which they are encountered in the event history). The simulation time (*Sim Time* column) shows either a negative value, which indicates a date of rank for a promotion occurring prior to the simulation start time, or a positive value, which represents a date of rank generated by a promotion within the simulation.[11] New entities created by the model are listed beginning in row 25.

As an example of the features found in the model, row 24 in Figure 6.1 shows a "New 32" entity being promoted to O-7 at simulation time 2.062627. This promotion was triggered by the promotion of "Starting Inventory 14" to O-8 (row 23), promotion of "Starting Inventory 7" to O-9 (row 22), and retirement of "Starting Inventory 13" in the grade of O-9 (row 21). In Figure 6.2, we see on row 32 that "New 32," at the tail end of the daisy chain described above, would have had a highly successful simulated career with a promotion to O-10 at simulated time 9.093427 (row 32).

[11] The actual dates of rank (DOR) shown in the DOR column are the dates of rank held by the officers in the starting inventory at the beginning of the simulation. Entities with positive values in the *Sim Time* column were promoted during the run of the model, while those with negative values were not promoted. In the latter case, the negative simulation time value corresponds to their date of rank.

Figure 6.2. General Officer List from the General Officer Lifecycle Flow Model (Basic Version)



	A	B	C	D
1	Name	Grade	DOR	Sim Time
2	Starting Inventory 20	10	1-Oct-20	-2.20020689
3	Starting Inventory 22	10	2-Nov-22	-0.11396459
4	Starting Inventory 5	9	7-Aug-20	-2.35078868
5	Starting Inventory 10	9	21-Oct-20	-2.14544988
6	Starting Inventory 15	10	23-Nov-20	0.942846
7	Starting Inventory 13	9	13-Aug-21	-1.33504604
8	Starting Inventory 21	9	2-Aug-22	-0.36584686
9	Starting Inventory 3	8	2-Aug-20	-2.36447794
10	Starting Inventory 6	9	7-May-21	0.942846
11	Starting Inventory 11	8	6-Jul-21	-1.43908437
12	Starting Inventory 19	10	17-Feb-22	2.919574499
13	Starting Inventory 17	9	29-Sep-22	1.621832371
14	Starting Inventory 23	9	29-Sep-22	1.690279126
15	Starting Inventory 1	7	1-Oct-14	-8.20157582
16	Starting Inventory 8	7	2-Mar-19	-3.7854225
17	Starting Inventory 4	10	3-Jul-19	5.734084606
18	Starting Inventory 2	7	1-Nov-19	-3.11738691
19	Starting Inventory 7	9	6-Aug-20	2.634837151
20	Starting Inventory 9	8	25-Jun-21	0.942846
21	Starting Inventory 12	8	15-Dec-21	1.621832371
22	Starting Inventory 14	8	3-Jul-22	1.621832371
23	Starting Inventory 16	8	2-Sep-22	1.690279126
24	Starting Inventory 18	10	1-Oct-22	5.939423561
25	New 25	8		2.634837151
26	New 26	9		5.383639336
27	New 27	9		5.734084606
28	New 28	7		0.603352427
29	New 29	9		6.278916836
30	New 30	7		0.945584178
31	New 31	9		5.939423561
32	New 32	10		9.093427658

Although the model has stochastic elements, it is not reiterated with the frequency required to produce statistically valid distributions of its outcomes. Apparently, the variances of the input distributions (the time-to-retire and time-to-promote) distributions are small enough to produce relatively consistent outcomes from each single-iteration run of the model.

This version of the model simulates only the pin-on dates of promotions. For entities promoted to grade O-8 or O-7, there would be a preceding selection date—the date of a promotion board—but such board actions are not included in the basic version. The utility of the model is its depiction of the expected number of promotions in each year of the simulation. This information can be used to plan the timing and frequency of promotion boards and the number to be selected.

The advanced version of the model, implemented either as an elaboration of the Excel-based basic version or recoded in Python, incorporates a promotion board feature. It allows for more-explicit examination of alternative board convening intervals and selection quotas. Moreover, for the U.S. Space Force, the small number of general officers presents a challenge in meeting statutory requirements for board membership (at least five officers, at least one grade higher than the officers being considered, and no service on consecutive boards). The model tracks board membership through the simulation period and illuminates the occasional infeasibility of forming a selection board given these requirements.

Chapter 7

The Dynamic Retention Model

The DRM, versions of which have been used at RAND since the 1980s to evaluate the impacts of compensation on retention (Gotz and McCall, 1984; Mattock and Asch, 2023), is an evolutionary advancement from the ACOL model discussed in Chapter 3. As Mattock and Asch (2023, p. v) indicate,

> [i]n the DRM, individuals make retention decisions in each year over their career and choose the alternative in each period—to stay or leave—that maximizes their utility, meaning they make the optimal choice each year given the information and opportunities available to them.
>
> . . . the DRM is formulated in terms of the parameters that underlie the retention decisionmaking process rather than on a specific compensation system and retention outcomes. When such a model is estimated with empirical data on individual retention decisions, it can be credibly used for counterfactual analyses, permitting assessments of alternative yet-to-be-implemented compensation systems.

The DRM has been applied to military personnel workforces (all services, active and reserve, officer and enlisted, and in special occupations, such as pilots), public school teachers, and state and federal employees. Notably, the model was used extensively to develop the provisions of the blended retirement system.

The model executes a maximum-likelihood algorithm to estimate its parameters using datasets that capture individual behaviors over multiple YOS. At each annual decision point, the model's representation of an individual making a retention decision compares the value of staying with the value of leaving. The value of leaving is the discounted present value of the stream of civilian earnings, plus any military retirement benefits that the member may have accrued, plus a shock term. The value of staying is the sum of a member's taste for active service, the military earnings for the current period, plus the discounted expected value of the maximum of staying or leaving in the following period, plus a shock term. The member stays if the value of staying is greater than the value of leaving. The model's parameters include those that characterize the taste and shock distributions. The parameters developed in the model are then used to simulate the cumulative probability of retention through each year of service, yielding a steady-state retention profile for a given policy environment (Mattock and Asch, 2023, p. 28).

Transformed parameters that are estimated in the maximum likelihood process are shown in Table 7.1 for a version of the model used to support decisions of the 13th Quadrennial Review of Military Compensation (QRMC) in 2020 (Mattock and Asch, 2023, p. 16). For computational advantages, most of the parameter values are estimated as logarithms or other special constructs. The values shown in the table transform the estimates to thousands of dollars.

Table 7.1. Transformed Parameter Estimates for Officers

Parameter	Army	Navy	Air Force	Marine Corps
Scale Parameter, Nest = τ	0.26	181.83	120.73	2.78
Scale Parameter, Alternatives within Nest = λ	109.15	29.96	52.67	78.68
Mean Active Taste = μ_a	–24.30	–20.06	–18.51	–14.14
Mean Reserve Taste = μ_r	–279.98	–55.37	–490.71	–138.94
SD Active Taste = σ_a	42.89	47.77	25.50	23.53
SD Reserve Taste = σ_r	191.57	48.66	324.13	90.75
Taste Correlation = ρ	0.58	0.74	0.42	0.51
Switch Cost: Leave Active < ADSO	–122.34	–180.42	–113.49	–133.39
Switch Cost: Switch from Civilian to Reserve	–425.02	–133.41	–248.92	–277.81
Personal Discount Factor β (Assumed)	0.94	0.94	0.94	0.94

SOURCE: Reproduced from Mattock and Asch, 2023, p. 37.

NOTE: Transformed parameters are denominated in thousands of 2007 dollars, with the exception of the taste correlation and personal discount factor. The scale parameter k governs the shocks to the value functions for staying and for the reserve-versus-civilian nest and equals $\sqrt{\lambda^2 + \tau^2}$. The means and SDs of tastes for active and reserve service relative to civilian opportunities are estimated, as are the costs associated with leaving active duty before completing ADSO and switching from civilian status to participating in the reserves. The personal discount factor was assumed to be 0.94 in these models. ADSO = active duty service obligation; SD = standard deviation.

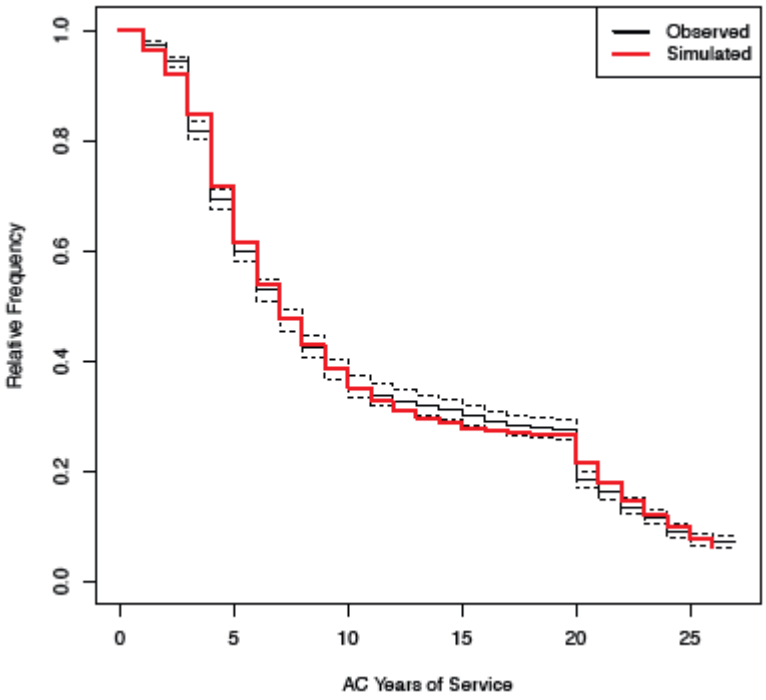
Inputs to the model include assumed pay streams for military and civilian workforces. In the 13th QRMC version, for example, Mattock and Asch (2023, pp. 28–29) report the following:

> For civilian pay opportunities for enlisted personnel, we used the 2007 median wage for full-time male workers with associate's degrees. For officers, we use the 2007 80th percentile of basic pay for full-time male workers with a master's degree in management occupations for civilian pay. . . . [For military work experience w]e used 2007 military pay tables.

The 13th QRMC version of the model included a grade dimension. Recognizing the complexities of including grade in an inventory model, as discussed in previous chapters, Mattock and Asch (2023, p. 30) chose the simplification of assuming that promotions to a grade occur in a single representative year.

To verify that the estimated parameters faithfully capture observed behavior, cumulative retention probabilities derived from the model are compared with the cumulative retention rates derived from the sample data. Figure 7.1 illustrates one such comparison from the 13th QRMC version of the model.

Figure 7.1. Model Fit Results—Active-Component Air Force Officers



SOURCE: Reproduced from Mattock and Asch, 2023, p. 45.
NOTE: Dotted lines represent 95-percent confidence intervals. AC = active component.

The DRM is computationally intensive. Important advances from the earlier Gotz-McCall version to the ones in use at the time of this writing were made possible only through the availability of more capable hardware and software. Opportunity for significant future refinements, in turn, depend on further advances in computing power (Mattock and Asch, 2023, p. 72).

Chapter 8

Statistical Versus Algorithmic Modeling

In a classic 2001 article, Leo Breiman observed that "[t]here are two cultures in the use of statistical modeling to reach conclusions from data. One assumes that the data are generated by a given stochastic data model. The other uses algorithmic models and treats the data mechanism as unknown" (Breiman, 2001, p. 199). Traditionally, these branches of the field of statistics are referred to as parametric statistics and nonparametric statistics, respectively. Parametric statistical modeling (e.g., linear regression, logistic regression, or more complex maximum-likelihood estimators such as the DRM) describes response variables as a function of predictor variables, random noise, and parameters using some chosen functional form. An algorithmic (i.e., nonparametric) model constructs a black box (e.g., a decision tree, gradient boosting, neural net, or some other form of machine learning [ML]) that best predicts an outcome given a rich array of related data (Breiman, 2001, p. 199). Commentary on Breiman's article typically notes that "[s]impler [statistical] models may be better for interpretation, but complex [algorithmic] ones are usually better for prediction" (e.g., Raper, 2020, p. 36). Notably, the algorithmic methods do not provide standard deviations of variables, which hinders testing for significance or calculation of confidence intervals. Such methods as bootstrapping may be applied to understand estimation error (Efron and Tibshirani, 1994); however, such an approach is time and resource costly, requiring thousands of replications of what may already be a complex ML algorithm. Where available, Bayesian nonparametric alternatives, such as Bayesian Additive Regression Trees, provide Monte Carlo chains as output that allow for the construction of credible intervals and estimates of posterior error (Chipman, George, and McCulloch, 2010).

This chapter provides examples of both parametric statistical models and analytic models, which both focus on retention as the predicted outcome. The parametric statistical model presented used linear regression to ascertain the factors important in determining the retention of Air Force enlisted personnel in aircraft maintenance career fields. The algorithmic modeling effort explored various ML approaches to developing general officer and enlisted retention forecasts.

Parametric Statistical Modeling

Statistical models can vary in the breadth of their focuses. While one class of retention models, such as the DRM, is used to deepen understanding of how a single variable or small set of covariates affects retention in a workforce, another class highlights the relative impact of a wide array of individual and environmental characteristics. The example of parametric statistical modeling presented here falls in the second class, which is more generally comparable to the algorithmic modeling example presented later. The parametric modeling example addressed the concerns of

managers of the Air Force aircraft maintenance, logistics, and munitions functional area who were apprehensive about the retention of sufficient experience in their enlisted workforce, particularly as the impacts of the blended retirement system emerged. They sought a deeper understanding of the factors that might affect retention.

The parametric modeling approach was a logistic regression model implemented in Stata (Robbert, Tong, and Hardison, 2022).[12] Separate regressions were developed for reenlistment decisions in three zones: 3–5 YOS, 6–9 YOS, and 10–13 YOS. An array of individual and environmental predictors was assembled, falling into five broad categories (Robbert, Tong, and Hardison, 2022, p. 11):

1. military characteristics
2. aptitude
3. performance quality indicators
4. demographic, family, and stressor variables
5. geographic and economic factors.

Logistic regression coefficients do not lend themselves to ready interpretation. Accordingly, the average marginal effect, which can be calculated from the coefficients, is commonly used to present the relative impacts of the predictor variables. Robbert, Tong, and Hardison (2022) presented the average marginal effects graphically, as indicated in Figure 8.1 for the 3–5 YOS band and one of the broad categories listed above.

[12] Logistic regression is used when the outcome of interest is binary, which is, in this case, stay or leave reenlistment decisions. The results can be transformed to indicate the probability of one of the binary outcomes.

Figure 8.1. Marginal Retention Probabilities for Military Characteristics Variables, Three to Five Years of Service

SOURCE: Reproduced from Robbert, Tong, and Hardison, 2022, p. 12.
NOTES: ACC = Air Combat Command; AET = Air Education and Training Command; AFE = U.S. Air Forces in Europe; AMC = Air Mobility Command; MTC = Air Material Command; OTH = other; PAF = Pacific Air Forces; SOC = Air Force Special Operations Command; SPC = Air Force Space Command; ADSC = active duty service commitment; SRB = selective reenlistment bonus. The range of vertical axis values for three to five YOS is 30–60 percent except where indicated by a red shading over the value. Dotted lines and whisker bars indicate 95-percent confidence intervals.

Another interesting display of results in this study contrasted individuals with high versus low propensity to reenlist. Individuals were rank-ordered by their overall predicted probability of reenlistment. The prevalence of various characteristics in the high (top decile) and low (bottom decile) in this rank-ordering was observed. Table 8.1 shows this result for another of the broad categories listed above, in this case for the 6–9 YOS zone.

Table 8.1. Observations with High and Low Propensity to Reenlist, with Six to Nine Years of Service, by Demographic, Family, and Stressor Characteristic

	Average Value or Proportion with Characteristic	
Characteristic	**High PTR**	**Low PTR**
Married	76%	43%
Military spouse	10%	5%
Female	4%	8%
Child in household	37%	10%
Average age	28.1	25.1
Racial/ethnic minority	32%	24%
At least three years of college credit	47%	24%
Average days per year deployed	7.4	0.3

SOURCE: Reproduced from Robbert, Tong, and Hardison, 2022, p. 25.
NOTE: PTR = propensity to reenlist.

Interestingly, this project also incorporated a second analysis using a version of the DRM specific to the occupational groups addressed in the project. The DRM was configured to project retention outcomes under both the blended and legacy retirement systems. As expected, given that the blended retirement system, including its mid-career retention bonus, was calibrated to produce retention results similar to the legacy retirement system, the DRM modeling in this project showed similar retention outcomes for both systems.

Algorithmic Modeling

Advances in data analytics have made ML algorithms readily available as nonparametric tools for relating individual and group characteristics to retention. ML algorithms can detect entity-level variations in retention as a function of numerous variables, at the expense of less insight into the relationships between the variables and the retention outcomes.

Schulker et al. (2021) explored the use of ML for predicting individual and group retention in Air Force officer and enlisted workforces. They tested several ML methods (general linear models, K-nearest neighbors, naïve Bayes, random forest, extreme gradient boosting [XGBoost] [Chen and Guestrin, 2016], and recurrent neural networks) before settling on XGBoost as their preferred method. The model assigned one- and three-year separation probabilities to each individual in the starting inventory as a function of 107 and 111 predictor variables for officers and enlisted personnel, respectively (Schulker et al., 2021, pp. 17–20). For any subgroup identifiable in the data, a subgroup retention rate can be calculated by averaging across the retention probabilities of individuals in the subgroup.

Table 8.2 shows the 20 variables they identified as having the largest retention impacts, measured as the relative improvement in prediction accuracy. In additional analysis, they confirmed that more-parsimonious models using the ten most-important variables would predict almost as well as the full

set of more than 100 variables. Notably, the ten-variable models predicted one-year and five-year group outcomes better than the three-year moving averages by Air Force specialty code (AFSC) and year of service used predominantly by the Air Force for retention forecasts (Schulker et al., 2021, p. 23), with the added advantage that retention rates can be derived for more finely grained subgroups definable with any variables either contained within the predictor set or linkable to the predictors.

Table 8.2. Variable Importance in Officer and Enlisted Models

Variable	Source	Category	Officer Gain (%)	Enlisted Gain (%)
Separation effective date listed	MilPDS	Collective characteristics	36.6	13.5
Reenlistment eligibility status	MilPDS	Collective characteristics	—	17.7
Max. ADSC time remaining	MilPDS	Collective characteristics	9.1	3.0
Separation eligible	MilPDS	Collective characteristics	5.0	5.7
3Y Ave separation rate by AFSC and YOS	MilPDS	Collective characteristics	3.9	4.5
Max. enlistment term time remaining	MilPDS	Collective characteristics	—	4.2
3Y Ave separation rate by AFSC and YOS among separation eligible individuals	MilPDS	Collective characteristics	2.3	1.8
YOS	MilPDS	Collective characteristics	2.2	1.5
Age	MilPDS	Collective characteristics	2.5	—
Duty AFSC	MilPDS	HR systems and practices	1.8	1.6
Location	MilPDS	Collective characteristics	1.7	1.5
Reenlistment eligibility status group	MilPDS	Collective characteristics	—	3.2
Enlisted performance report ratings	MilPDS	Collective characteristics	—	3.2
Previous year separation rate among AFSC age-group cohort	MilPDS	Collective characteristics	1.6	1.5
Rank	MilPDS	Collective characteristics	1.7	1.4
Nondeployable—retainability[a]	MilPDS	Collective characteristics	2.1	—
Nondeployable—physical	MilPDS	Collective characteristics	1.4	1.5
Career field manning	MilPDS	Collective characteristics	1.7	1.2
BMI	AFFMS	Collective characteristics	1.4	1.5
Aerobic fitness test performance	AFFMS	Collective characteristics	1.3	1.5
Local median compensation	MilPDS and ACS	Environmental characteristics	1.3	1.2
Core ID (officer) or control AFSC (enlisted)	MilPDS	HR systems and practices	—	1.3
Promotion status[b]	MilPDS	HR systems and practices	2.2	—
Percentage core ID or control AFSC that is female	MilPDS	Collective characteristics	1.1	—
Medal count	MilPDS	HR systems and practices	1.2	—

SOURCE: Reproduced from Schulker et al., 2021, pp. 22–23.
NOTE: 3Y Ave = three-year average; ACS = American Community Survey; ADSC = active duty service commitment; AFFMS = Air Force Fitness Management System; BMI = body mass index; HR = human resources; ID = identifier; max. = maximum; MilPDS = Military Personnel Data System.
The table omits percentages if the variable did not fall in the top 20 for both officer and enlisted models.
[a] Retainability affects officer and enlisted capacity to deploy in cases in which members have a date of separation that would prevent them from completing the required deployment duration.
[b] Promotion status indicates whether an officer has been considered/selected for promotion to the next grade and for which zones.

Chapter 9

The Recruiting Resource Model

Among the military services, the Army typically faces the greatest challenge in meeting recruiting objectives, in large measure because of its much greater annual accession requirement. Accordingly, it has the greatest interest in maximizing the effectiveness of its investments in recruiting resources. The result has been a sustained emphasis on modeling the relationship between recruiting resources (recruiters, advertising, and enlistment bonuses) and accession outcomes in the Army. The Recruiting Resource Model (RRM) is the contemporary embodiment of that effort. The RRM line of research is an active one, and RAND has published multiple versions of the model. As of this writing, there are published versions for the Regular Army (Knapp et al., 2018; Ward et al., 2023) and for the U.S. Army Reserve (Orvis et al., 2021). This tool covers only the open source versions published at the time of writing. However, a forthcoming publication will update the data used in the RRM and integrate the latest active and reserve versions of the model.

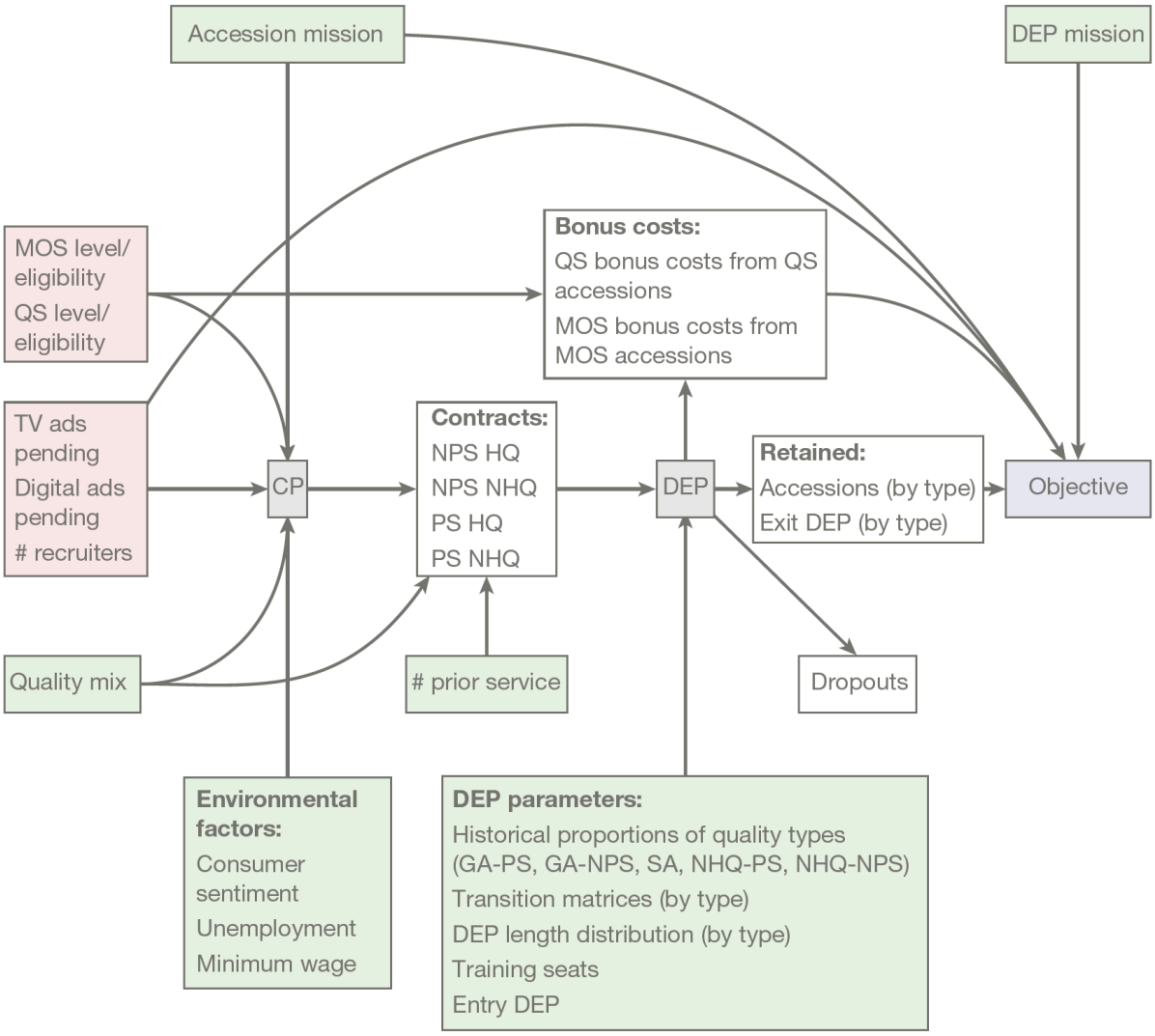
Ward et al. (2023, p. 3) describe the model as follows:

> The Recruiting Resource Model (RRM) . . . [comprises] three distinct sub-models: contract production, Delayed Entry Program (DEP) dynamics, and cost allocation. The contract production model (CPM) weighs trade-offs between recruiting conditions and the recruiting resources used to produce [high-quality] and [non-high-quality] enlistment contracts. The DEP dynamics model assigns differential times in the DEP and rates of attrition according to contract characteristics . . . . The third model, cost allocation, calculates costs per accession for a given FY.

The sub-models use three different estimation methods. In the most recent versions, the CPM was estimated using logged values of a Cobb-Douglas production function in a fixed effects regression (Ward et al., 2023, pp. 62–63). The earliest version of the model used a nonlinear least squares estimation method (Knapp et al., 2018). Estimation of the CPM requires accurate monthly data at the recruiting company level on the number of recruiters, spending on advertising for Army recruiting, and bonus spending. Though the quality of advertising data has markedly improved since 2019, historically, it has been a limiting factor on the breadth of the RRM's marketing assessments. Attempts to construct a version of the RRM for other services, including the U.S. Air Force, will hinge on the quality and breadth of available advertising data.

The third sub-model, which is an optimization model, determines the cost-minimizing mix of bonuses, advertising, and recruiter spending, plus a penalty for monthly over- or under-production (Ward et al., 2023, pp. 71–72). Ideally, the optimizer will produce the cost-minimizing combination of recruiting resources that makes the Army's accession mission and DEP goal exactly. Figure 9.1 provides a graphical overview of the optimization model.

Figure 9.1. Graphical Overview of the Optimization Model



SOURCE: Reproduced from Ward et al., 2023, p. 72.
NOTE: CP = contract production; DEP = Delayed Entry Program; GA = graduate alpha; HQ = high-quality; MOS = military occupational specialty; NHQ = non-high-quality; NPS = non–prior service; PS = prior service; QS = quick-ship; SA = senior alpha. Pink-shaded nodes indicate variables that are optimized over. Green-shaded nodes indicate variables that are set by the user and define an excursion.

The RRM has several limitations, which are discussed at length in the conclusion of Ward et al. (2023). We touch on only the most important here and direct interested readers to the published RRM reports for further details. The first limitation is that the relationship between variables can change over time. For example, the published RRM reports, which are estimated using data from FYs 2013 to 2018, all found a strong return to television advertising or, more recently, digital marketing; more-recent shifts in patterns of television and digital media consumption by teenagers could reasonably lead this to change over time. The second is that the CPM is estimated using observational data; therefore, the parameters representing the "return" to each type of recruiting resource do not

represent causal estimates. While it is likely that the general patterns hold (i.e., that advertising is the most cost-effective resource and bonuses are the least cost-effective resource), the exact spending levels suggested by the optimization routine would not necessarily produce the exact number of contracts and accessions predicted by the model. Finally, because of computational constraints, the optimizer used in the currently published reports is a local, rather than global, optimizer. This means that it is possible that there are combinations of resources that could both achieve the Army's mission and be less expensive than the optimizer's output.

Chapter 10

Disparate Impact Analyses

The potential for racial, ethnic, and gender disparities in the outcomes of personnel processes (particularly promotions and other selection processes, but also accessions and retention) has received significant attention in RAND research. A body of this research has employed an analytic approach using an equivalent-group framework, sometimes referred to as a look-alike analysis. Recent reports looked at officer retention and promotions in the U.S. Coast Guard (Lim et al., 2021) and developmental education selection boards in the U.S. Air Force (Conley et al., 2022). A more in-depth discussion of the methodology can be found in Lim et al. (2014), which examined Air Force officer retention and promotion outcomes.

The methodology involves two steps (Lim et al., 2021, p. 155):

i. The first step is used to create a White male comparison group with records that mirror the [underrepresented minority] (URM) group as closely as possible on relevant available variables that are informative of selection promotion.
ii. In the second step, [the authors] modeled the promotion outcomes for the URM personnel and their White male comparison group to determine whether the comparisons with similarly situated records have the same probability of promotion or, instead, an unexplained difference in outcomes between the URM group and their comparison group.

The first step uses *propensity scoring* (Rosenbaum and Rubin, 1983; Rosenbaum and Rubin, 2023) to create a synthetic comparison group of majority members that looks similar to a minority group on observed relevant career and demographic characteristics. The propensity score is the probability that an individual with a given set of characteristics would be a member of a minority group. When weighted by the odds of being in the minority group, the majority group can serve as a counterfactual comparison to the minority group (Lim et al., 2014, pp. 26–27). In their analysis of gender differences in retention outcomes, Lim et al. provided examples of this weighting, as shown in Table 10.1.

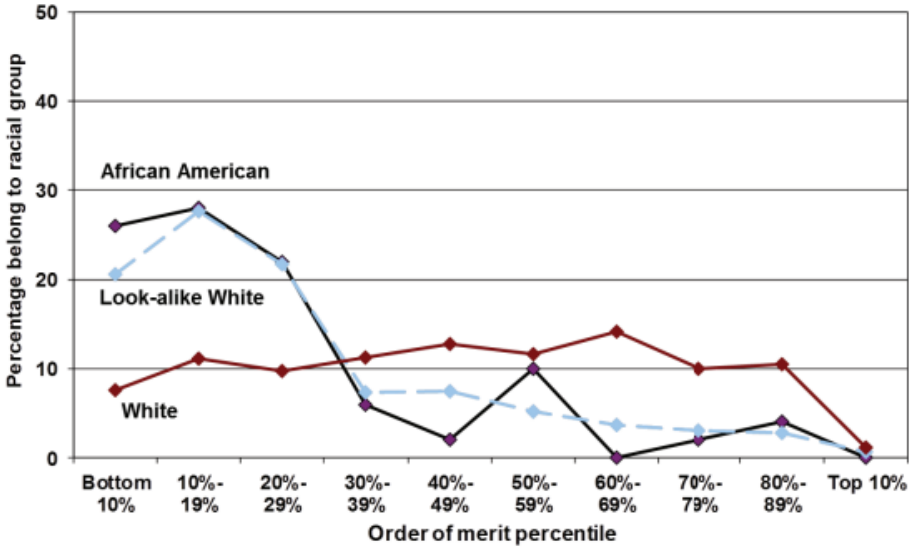
Table 10.1. Distribution of Selected Characteristics by Gender and Counterfactual Groups of Air Force Line Officers at Eight Years of Service

Characteristic	Observed Men	Observed Women	Weighted Men
Source of commission			
USAFA	22%	12%	12%
OTS	24%	18%	18%
ROTC	42%	34%	34%
Other	13%	36%	35%
Marital status			
Divorced	4%	12%	13%
Married to a service member	41%	47%	47%
Married to non–service member	41%	18%	18%
Single	14%	23%	23%
Number of children	1.12	0.63	0.62

SOURCE: Reproduced from Lim et al., 2014, p. 27.
NOTE: USAFA = U.S. Air Force Academy; OTS = Officer Training School; ROTC = Reserve Officer Training Corps. Some categories may not add up to 100 percent because of rounding.

In a similar example found in a promotion analysis, Lim et al. demonstrated that propensity scoring may not create a perfectly matched look-alike comparison group. See Figure 10.1.

Figure 10.1. U.S. Air Force Academy Order of Merit, by Race, Among Line Officers (1998–2005)



SOURCE: Reproduced from Lim et al., 2014, p. 38.
NOTE: "Look-alike" groups refer to weighted comparison groups used for statistical analysis.

For binary outcomes, such as promotion, the second step uses weighted logistic regression to remove any small remaining differences between the minority group and the counterfactual majority group, such as those illustrated in Figure 10.1. The weights that are derived in the first step are used for the majority group, and members of the minority group receive a weight of one. The regression "includes all available characteristics as well as an indicator as to whether each observation belongs to the minority group. A regression coefficient for this minority group indicator that differs significantly from zero would indicate that a difference between minority and nonminority outcomes still exists after accounting for all the available characteristics" (Lim et al., 2014, p. 38). Finally, the minority group is recoded to instead be members of the majority group, and the regression coefficients are used to predict counterfactual outcomes for the minority group. Comparison of these predicted outcomes with the minority group's actual outcomes indicates the direction and magnitude of any significant differences (Lim et al., 2014, p. 38).

For continuous outcomes, the second step is nearly identical, with a weighted linear regression model implemented. Here, the final step of predicting the counterfactual is not necessary, as the regression coefficient for the minority group indicator captures not only whether a difference between minority and nonminority outcomes remain but also the direction and magnitude of this difference.

These two steps together constitute the standard *doubly robust* estimation technique (Bang and Robins, 2005; Kang and Schafer, 2007) to estimate propensity weighted counterfactual outcomes for causal inference (McCaffrey, Ridgeway, and Morral, 2004). However, the interpretation of these disparate impact analyses is not a true causal relationship because individuals cannot be assigned to the majority and minority groups.

Using these techniques, studies generally find that the underlying processes are fair but that disparate outcomes emerge and are largely attributable to characteristics other than the minority group indicator.

Chapter 11

Manpower Requirements Modeling

This chapter shifts to a different focus of modeling efforts. Whereas the previous chapters described models that focus on the *supply* side of personnel resource management, the *demand* side—commonly referred to as *manpower requirements determination*—has received much less attention within RAND's human capital management programs.

Contrasts in Manpower Modeling

In this chapter, we contrast three varieties of manpower models. One approach, which is typically used in unique work environments, relies on relatively straightforward workload measurement. A contrasting approach, which is typically used in work environments that are replicated in multiple settings, relies on statistical analysis of extensive workload measurement data.[13] A third approach, which is useful when timeliness of service provision is a key issue, can be found in queuing theory.

In recent years, RAND has produced two bodies of workload measurement and compilation. One concerns several agencies within the U.S. Department of Homeland Security (DHS).[14] The other concerns staff from the Directorate of Intelligence (J2) in the U.S. Northern Command and the U.S. European Command. Both bodies of work focus on headquarters staff activities in which virtually every office that was evaluated in these studies performed a unique set of processes; these staff activities contrast with field activities in which staff from many offices perform replications of standard functional processes. Accordingly, modeling the workload consisted largely of describing the processes and breaking them down into discreet tasks, measuring the frequency and duration of tasks within each process, and compiling the data to provide estimates of required workforce sizes. Because of the uniqueness of the processes performed by staff activities, statistical approaches to manpower requirements modeling, such as queuing models or regression techniques, have been employed very sparingly.

In contrast, statistical modeling approaches rely on large datasets that contain many repeated measurements of the durations of similar tasks and distributions of task frequencies under varying conditions. Types of this approach include simulation models, queuing models, and regressions of workload estimates on measurable and predictable workload drivers. A prominent example of statistical modeling is the Logistics Composite Model (LCOM), which was developed at RAND in

[13] The Air Force has a well-developed and extensively documented set of manpower standards development processes. See Air Force Manual 38-102, *Manpower and Organization Standard Work Processes and Procedures*, 2024, in which various types of both varieties are described.

[14] See, for example, Robbert and Reininger, 2020; Lim et al., 2021.

the 1960s (Fisher et al., 1968) and has been in continuous use within the U.S. Air Force to the present day (Air Force Manual 38-102, 2024).

Queuing models have been used in some special cases in work for DHS clients, but, so far, they have not appeared in published work. It and the two varieties introduced above are described in the remainder of this chapter.

Workload Measurement in Unique Activities

Workload measurement modeling within a specific function or office proceeds through these steps:

- Determine the processes for which the office is responsible.
- Develop process maps that depict the steps within each process.[15]
- Obtain data regarding the frequency of each process and subprocess and the average duration of each step in the process for both current and planned (or desired) workloads.[16]
- Calculate the sum-product of task frequencies and durations for both current and planned (or desired) workloads.
- Determine the *man-hour availability* (availability to perform primary duties) of workers in the function.
- Divide the sum-product of task frequencies and durations by the man-hour availability to determine the required workforce for both current and planned (or desired) workloads.
- Calibrate the model by comparing the current workforce requirement calculation with the size of the actual workforce performing the work. If the calculated current requirement is not reasonably close to the actual workforce, review and adjust task durations, frequencies, or both.
- After calibration of the current workload requirement, review planned (or desired) task frequencies or durations and adjust as necessary.

Figure 11.1 provides a sample process map. The map uses a very limited set of process symbols and depicts only the tasks that are executed within the specific office or activity being measured (i.e., it does not include "swim lanes" used to show interaction of processes among multiple activities).[17] Typically, the process maps were developed using Microsoft Visio, which allowed for process

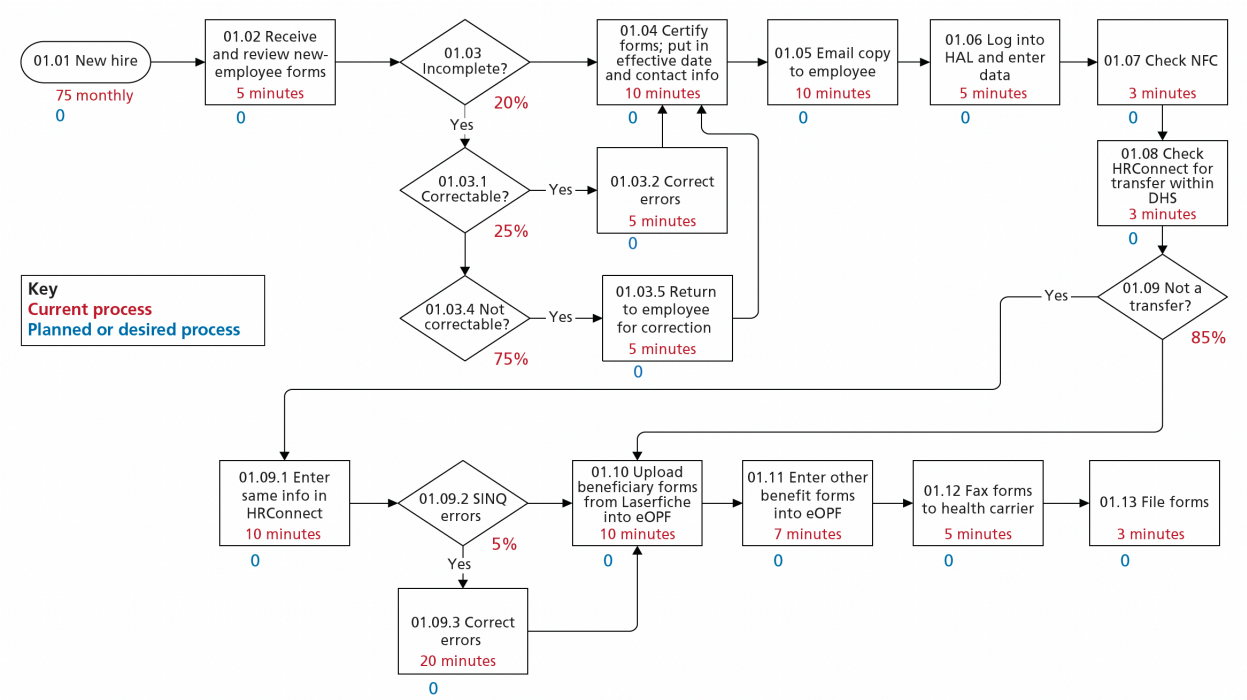
[15] The work for the two J2 directorates was classified and accomplished through a streamlined process. Process maps were not developed, and workload frequency and duration estimates were made at the level of what the intelligence community generally understands to be a specified or implied *task*, but a task that is comparable to what RAND analysis considers a *process* in other manpower modeling efforts. These simplifications were made to permit the project to be executed within the time and resources of both the study teams, the supervisors, and subject-matter experts within the studied directorates. The description of the work measurement process that is provided in this report is the more detailed process used for the DHS agencies rather than the streamlined process used for the J2 directorates.

[16] Planned or desired workloads are used when there is an expected or desired change from current workloads, typically because of an increase in task frequencies, unacceptable processing queues, or insufficient quality of products or services.

[17] This process map was developed early in Homeland Security Operational Analysis Center's (HSOAC's) series of manpower modeling projects for DHS agencies. Subsequent project teams refined the symbology somewhat, but published examples are not available.

frequencies and task durations to be captured, displayed on the process maps, and exported in Excel format for further processing.

Figure 11.1. Sample Process Map

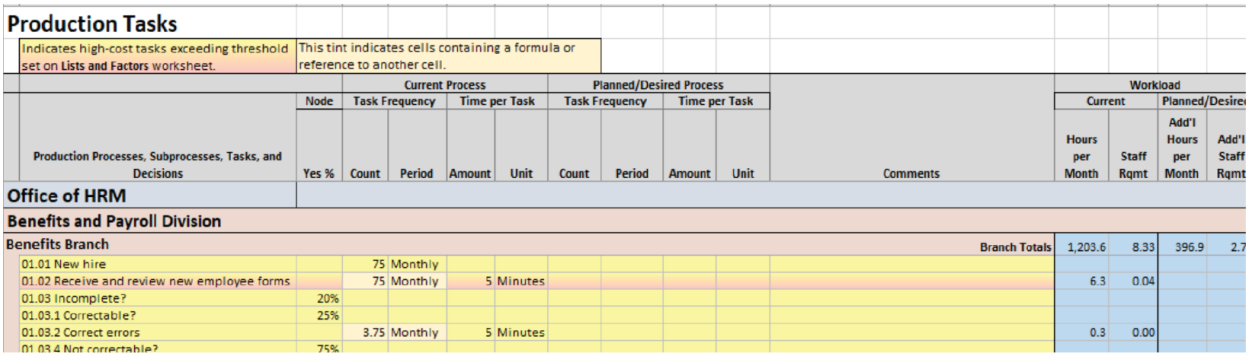


SOURCE: Reproduced from Robbert and Reininger, 2020, p. 5.
NOTE: HAL = Health and Life (a Microsoft Access database); NFC = National Finance Center; SINQ = suspense inquiry. HRConnect is a PeopleSoft payroll system. Laserfiche is a database of scanned beneficiary forms that serves as a backup to the electronic official personnel folder (eOPF).

Figure 11.2 provides a sample of an Excel spreadsheet used to compile the frequency and duration data. Frequency and duration data are entered in the yellow columns. Sum-products of task frequencies and durations are shown in the blue columns in both hours per month and staff requirements (fractions of a man-year).[18]

[18] As with the process maps, subsequent project teams introduced some refinements in the configuration of the worksheet.

Figure 11.2. Sample Task Frequency and Duration Data Embedded in an Excel Worksheet



Production Tasks

Indicates high-cost tasks exceeding threshold set on **Lists and Factors** worksheet.

This tint indicates cells containing a formula or reference to another cell.

Production Processes, Subprocesses, Tasks, and Decisions	Node Yes %	Current Process: Task Frequency Count	Current Process: Task Frequency Period	Current Process: Time per Task Amount	Current Process: Time per Task Unit	Planned/Desired Process: Task Frequency Count	Planned/Desired Process: Task Frequency Period	Planned/Desired Process: Time per Task Amount	Planned/Desired Process: Time per Task Unit	Comments	Workload: Current Hours per Month	Workload: Current Staff Rqmt	Workload: Planned/Desire Add'l Hours per Month	Workload: Planned/Desire Add'l Staff Rqmt
Office of HRM														
Benefits and Payroll Division														
Benefits Branch										**Branch Totals**	1,203.6	8.33	396.9	2.7
01.01 New hire		75	Monthly											
01.02 Receive and review new employee forms		75	Monthly	5	Minutes						6.3	0.04		
01.03 Incomplete?	20%													
01.03.1 Correctable?	25%													
01.03.2 Correct errors		3.75	Monthly	5	Minutes						0.3	0.00		
01.03.4 Not correctable?	75%													

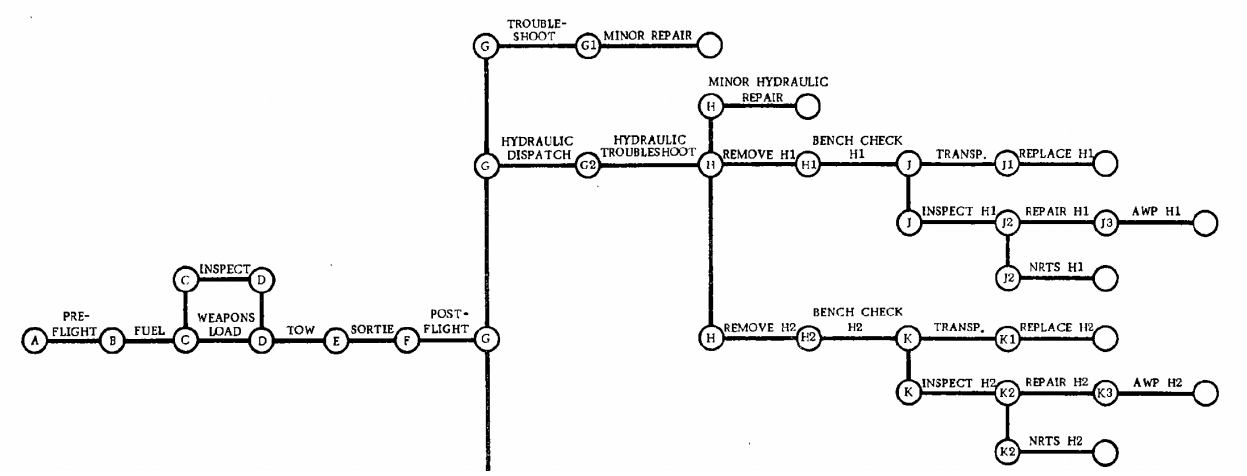
SOURCE: Reproduced from Robbert and Reininger, 2020, p. 13.

The Logistics Composite Model

LCOM was constructed to determine the resource needs of logistics functions. As succinctly stated by its developers, it "contains representations of flying operations for a mix of aircraft and sortie types, flight-line and shop repair processes . . . and supply functions in support of maintenance. Classes of resources explicitly identified . . . include aircraft, personnel, spare parts, [aerospace ground equipment], and facilities" (Fisher et al., 1968, p. 4). It was developed cooperatively by RAND and the Air Force Logistics Command (Fisher et al., 1968, pp. 3–4). It includes a *pre-processor* to prepare data and sortie requirements for use in a *simulation program* and a *post-processor* to make output data available for further analysis (Fisher et al., 1968, p. v).

A key input to the model is a *task network* (depicted in Figure 11.3), which is the functional equivalent of a process map (depicted in Figure 11.1). As with a process map, the task network contains probabilities for the various branches at points where the network diverges. A run of the model processes these nodes stochastically. The model also contains optimization algorithms intended to find maintenance policies that minimize resource consumption.

Figure 11.3. Sample of an LCOM Task Network



SOURCE: Adapted from Fisher et al., 1968, p. 13.
NOTE: This figure is truncated to enhance readability.

Aside from providing an interesting example of a statistical manpower modeling approach, LCOM is remarkable for its longevity. The original 1960s-era model was written in SIMSCRIPT, which is a computer simulation language developed at RAND (Markowitz, Hausner, and Karr, 1962). A contemporary version, the Logistics Composite Model Analysis Toolkit (LCOM ATK), is available from the Air Force Life Cycle Management Center in a form that can be executed on a desktop computer running Excel and Java (Defense Acquisition University, 2022). A useful description and critique of the manpower-related features of the model can be found in Dahlman, Kerchner, and Thaler, 2002.

Queuing Models

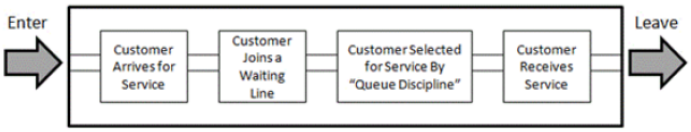
In manpower requirements studies for two DHS agencies, HSOAC researchers encountered work environments in which the timeliness of services provided was a key consideration.[19] One of these involved the timeliness of pre-employment processing of new hires. Time-to-hire is notoriously lengthy in federal government agencies (Jones, 2019), especially for sensitive positions that require security, medical, and other special screening steps. While some steps can be performed in parallel, some are necessarily sequential. The *time-to-hire* is the sum of the time spent waiting for service plus the time being serviced in each of the sequential steps. In another context, backlogs in processing Freedom of Information Act requests can far exceed statutory standards (Sager, 2020). In both cases, queuing theory was used to estimate the increase in manpower required to meet timeliness standards.

Figure 11.4 illustrates the general flow of a queuing system, whereas Figure 11.5 indicates the type of information needed to construct a queuing model. The key inputs are the customer arrival rate per unit of time and the customer service rate per unit of time. The useful outputs are the expected number of customers in the queue and the time spent in the queue. The service rate is the inverse of

[19] See Robbert and Reininger, 2020; Lim et al., 2021.

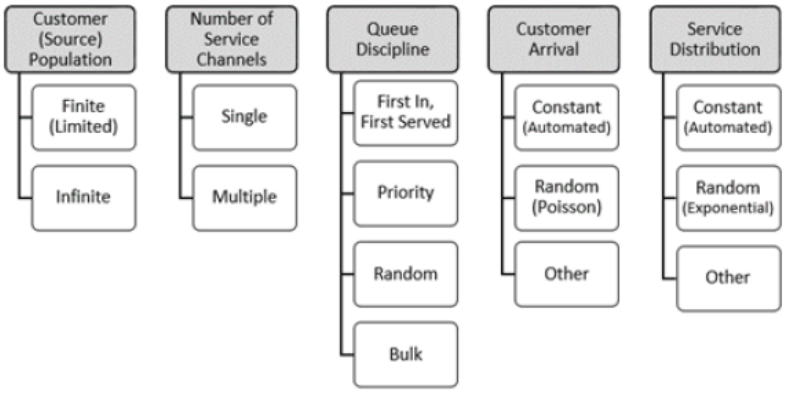
the time required to service one customer. The time to service a customer and the number of workers required to provide the service must be determined exogenously to the queuing model and would likely entail workload measurement approaches, as described in the previous two sections of this chapter. Specific equations used in the model depend on the various characteristics of the customer population and the servicing arrangements, as illustrated in Figure 11.4.

Figure 11.4. General Flow of a Queuing System



SOURCE: Reproduced from Air Force Manual 38-102, 2024, p. 137.

Figure 11.5. Types of Information Needed in a Queuing Model



SOURCE: Reproduced from Air Force Manual 38-102, 2024, p. 139.

Chapter 12

Personnel Costs in Inventory Models

In many analyses, the cost of comparative personnel inventories is an important consideration. The cost factors applied to a projected inventory depend on the level of detail at which the inventory is projected. Cost-relevant dimensions that may or may not be represented in a model include grade, YOS, and occupation.

In addition to *force* costs (the pay, allowances, and other ongoing costs of an inventory), *training* costs are also often an important element in military personnel inventory projections.[20] Two factors account for this. First, military inventory turnover rates are relatively high and will typically vary as a function of the contrasting policies examined in a model, so costs incurred to access new members are relevant to costing the policy alternatives. Second, in contrast to most military hiring contexts, the military services typically invest training in new recruits at costs ranging from modest to extraordinarily high, depending on the occupation.

Compensation Rates

An authoritative source for military rates of basic and special pays, allowances, and other compensation factors, current and historic, is the DoD's "Military Compensation" webpage (see DoD, undated). The Office of Personnel Management (undated) provides similar online information for civilians, but note that civil service salary and wage rates are much more differentiated by occupation, locality, and organization.

Composite Rates

Annually, the DoD Comptroller computes and publishes military personnel composite pay and reimbursement rates (OSD, 2023). The composite rates are unique to each military service and vary by grade. Within a grade, detailed pay and compensation will vary as a function of YOS, occupation, marital status, and other factors. The composite rates provide weighted averages across these factors in such elements as "basic pay, retired pay accrual, basic allowance for subsistence, basic allowance for housing, incentive and special pay, permanent change of station expenses, and miscellaneous pay" (McAndrew, 2023, Tab K-1, p. 1). [21] Rates are provided for several purposes, such as rates billable to other DoD and non-DoD organizations. The rate that is generally applicable to military personnel studies is the DoD Composite Standard Pay Rate.

[20] Training costs, viewed as an element to be added to force costs, are sometimes referred to as the *training tail*.

[21] Unfortunately, the Comptroller does not provide decomposition of the composite rates into these various elements; see the "Decomposition of Pay" section.

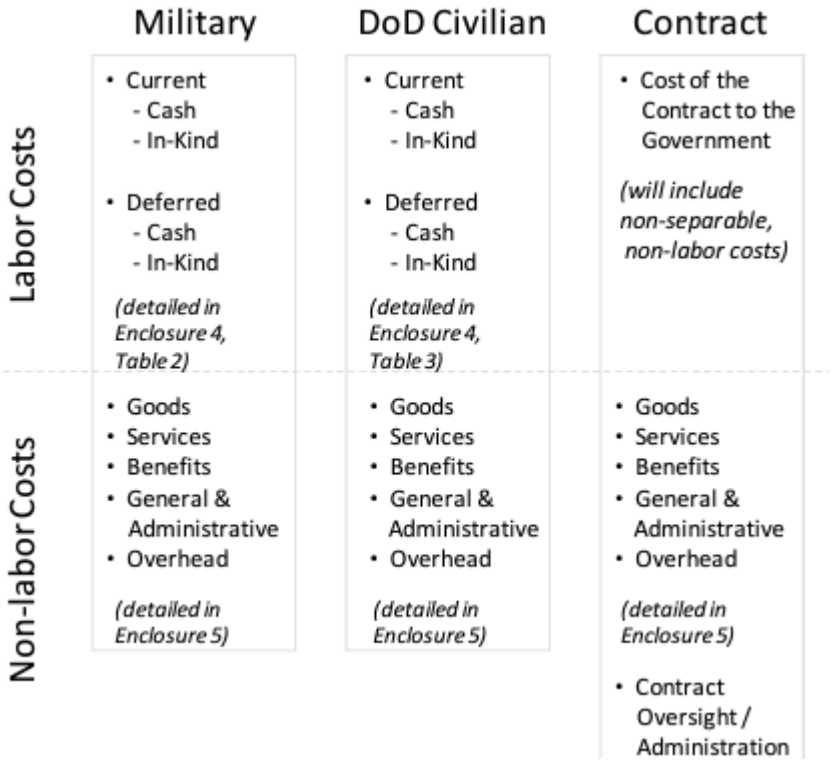
Fully Burdened Costs

The overview provided with DoD composite rate data states that "The DoD Composite Standard Pay Rate will be used when determining the military personnel appropriations cost for budget/management studies but should not be considered as the fully burdened cost of military personnel for the purposes of workforce-mix decisions" (McAndrew, 2023, Tab K-1). A fully burdened cost would include estimates of the per capita nonlabor and indirect labor costs of maintaining a direct-labor worker in an organization.[22] The Reserve Forces Policy Board (RFPB) (2013, 2019) has argued for the development of fully burdened costs for the purpose of comparing the costs of regular and reserve component personnel and has provided its estimates of such costs. The DoD Director of Cost Assessment and Program Evaluation (CAPE) has taken issue with the RFPB methodology (see memo included as Appendix D in RFPB [2019]). CAPE has done its own work on the full costs of active duty military personnel, civilian personnel, and contractors (but not reserve personnel) and also provides a Full Cost of Manpower tool on its website (OSD, undated).[23] Figure 12.1 indicates CAPE's summarization of the elements of full manpower costing.

[22] *Direct labor* produces the end products and services of an organization. *Indirect labor* provides overhead support.

[23] Access requires a DoD common access card with an appropriate certificate.

Figure 12.1. CAPE's Cost Elements of the Full Cost of Manpower



SOURCE: Reproduced from DoD Instruction 7041.04, 2020, p. 10.

An effort to provide the installation non-pay cost factors per supported individual can be found on the "AFI 65-503, Cost Factors" webpage of the Air Force Portal (SAF/FMC, 2018).[24] These factors may or may not be contained in CAPE's Full Cost of Manpower tool.

Decomposition of Pay

Some more-detailed inventory projection models may carry both grade and YOS dimensions, corresponding to the two dimensions found in military basic pay tables. Analysts seeking to provide force costs that are similarly differentiated can easily compute the sum of basic pays for an inventory by taking the sum-product of the inventory distribution and the basic pay table. To get a more complete cost estimate, the basic pay computation must be supplemented with a computation of non-basic pay elements. Unfortunately, DoD composite rates do not provide a breakdown between basic pay and non-basic pay elements. One approach for computing a grade-varying sum of non-basic pay elements is to compute the weighted (by year of service) average pay grade for an historic year of

[24] See Table A56-1 under the cost models heading at Air Force Deputy Assistant Secretary for Cost and Economics (SAF/FMC), 2018. If necessary, use "cost factors" as the search box entry. Access requires DoD common access card or password and registration with the portal manager.

service for which DoD composite rates are available. The weighted average basic pay rate for each grade can be subtracted from the DoD composite rate for each grade to find the sum of non-basic pay elements.

A more complete decomposition of the DoD composite rates is available from the office of the Air Force Deputy Assistant Secretary for Cost and Economics (SAF/FMC, 2018). As of this writing, the data for active duty personnel were updated in February 2023 and for reserve personnel in December 2020. The list of cost factors and the points of contact responsible for updating them is specified in Air Force Instruction 65-503 (2018), and tables containing the data are available on the Air Force Portal (SAF/FMC, 2018).[25] The composite rate by grade is decomposed into the following elements: basic pay, Medicare-eligible health care accrual, retired pay accrual, basic allowance for housing, basic allowance for subsistence, incentive special pay, permanent change of station, and miscellaneous.

Finally, the CAPE Full Cost of Manpower tool (OSD, undated) provides hyper-disaggregated costs for a single billet or for a group of billets assembled by the user. Although the process of extracting them might be somewhat tedious, this tool provides a means to get very specific cost factors that could then be merged or weighted as required to match the dimensions of an inventory model.

Training Costs

Air Force costs for various types of training are found at the same Air Force Portal webpage cited above for composite personnel costs. See Air Force Deputy Assistant Secretary for Cost and Economics (2024), Tables A18-1a and A18-1b, for enlisted and officer training data—both of which were updated in July 2024.

[25] Access requires a DoD common access card or password and registration with the portal manager.

Chapter 13

Choosing a Modeling Approach

Although new variants continue to emerge, any modeling requirement intended to support personnel policy analysis will likely benefit from familiarity with previous efforts described in this tool. Existing models described here may be sufficient to meet emerging needs or may provide points of departure for further development to meet current needs. As a minimum, this tool can help focus the literature review conducted at the beginning of a project.

In choosing a modeling approach, the taxonomy employed by the Naval Personnel Research and Development Laboratory (see Chapter 1) might be helpful. Table 13.1 indicates where we would place each of the models described in this tool in a similar taxonomy, expanded from the version in Chapter 1 to accommodate newer forms of modeling.

Table 13.1. Model Classification and Techniques Employed

		Stochastic		Probabilistic	Deterministic	
Model	**Chapter**	**Bulk-Flow**	**Entity**	**Analytic (Statistical/ML)**	**Analytic (Mathematical)**	**Mathematical Programming**
Acquisition Workforce IPM	2				x	
CAPM	3		x			
TFBL	4					x
Optimizing officer promotion	5					x
GOLF	6		x			
DRM	7			x		
Other retention models						
Logistic regression	8			x		
Algorithmic	8			x		
RRM	9			x		
Disparate impact analysis	10			x		
Manpower models						
Workload measurement	11				x	
LCOM	11		x			
Queuing	11			x		

NOTE: IPM = inventory projection model. The taxonomy shown in Figures 1.1 and 1.2 in Chapter 1 has been updated here. Modern ML models have been incorporated. The classifications here reflect that statistical models incorporate probability and uncertainty into estimation and produce predictions that reflect inherent variation. Some statistical and ML models, including those described in Chapter 10, incorporate multiple repeated draws from a distribution of interest to produce estimates, while others only require a single iteration for estimation.

For other modeling decisions, a consideration similar to Occam's razor should be applied. Fewer elements in a model entail simpler data retrievals, less chance of coding errors, and easier interpretability. Specifically, considerations should include the following:

- Avoid entity models, whose stochastic features generally require obtaining a distribution of results over many runs, if aggregate models will do.
- Avoid dimensionality (e.g., grade, YOS, occupational specialty) that is not relevant to the policy question being examined and is not needed to enhance the accuracy of projections.
- Avoid dynamic (multiyear) models if steady-state modeling will do. This is particularly relevant for examining policies whose impacts emerge well into the future.

- Use the simplest or most familiar software package that meets the need.
- If a model will be shared with a sponsor or other research institution, consider whether such software is available when choosing a platform.
- When coding, resist the urge to write the most elegantly compact code. With contemporary computing power, run time is seldom a critical consideration. Write code that breaks complex computations into steps that are easier for others to audit. Comment liberally.
- Construct well-organized archives for inputs, outputs, and model variants. Adopt a systematic labeling scheme early in the model development process. Preserve replicability.

With careful attention to these considerations, personnel inventory modelers can be well on their way to creating effective and reliable models that support human resource policy analysis.

Abbreviations

ACOL	annualized cost of leaving
AFR	Air Force Reserve
AFSC	Air Force specialty code
ANG	Air National Guard
CAPE	Cost Assessment and Program Evaluation
CAPM	Compensation, Accessions, and Personnel Management (model)
CPM	contract production model
DEP	Delayed Entry Program
DHS	U.S. Department of Homeland Security
DoD	U.S. Department of Defense
DRM	Dynamic Retention Model
FY	fiscal year
GOLF	General Officer Lifecycle Flow (model)
HSOAC	Homeland Security Operational Analysis Center
J2	Directorate of Intelligence
LCOM	Logistics Composite Model
LCOM ATK	Logistics Composite Model Analysis Toolkit
ML	machine learning
OSD	Office of the Secretary of Defense
QRMC	Quadrennial Review of Military Compensation
RegAF	Regular Air Force
RFPB	Reserve Forces Policy Board
RRM	Recruiting Resource Model
SAF/FMC	Air Force Deputy Assistant Secretary for Cost and Economics
TFBL	Total Force Blue Line (model)
YOS	years of service

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