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THESIS

ENHANCING PERSISTENCE WHEN OPTIMALLY SCHEDULING DEPOT-LEVEL REPAIR ACTIVITY FOR THE UNITED STATES MARINE CORPS

by

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June 2003

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The United States Marine Corps' ability to wage war and its warfighting effectiveness rely heavily on the availability of its tactical ground equipment. The Marine Corps optimizes the warfighting availability of its tactical ground equipment in its depot-level repair plan, which commits $450 million over a six-year horizon. Currently, small changes (for example, budget) to the input to this model produce non-intuitive revisions that are needlessly disruptive. The Marine Corps Materiel Command (MATCOM) recognizes this problem and has asked for enhancement of their current model to include persistent features. We show that turbulence can be reduced at little cost in warfighting availability. We also investigate an approximate, but very fast heuristic in lieu of mathematical optimization to solve this problem. A simple greedy myopic heuristic quickly produces nearly-optimal advice to the depot-level planning problem.

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ENHANCING PERSISTENCE WHEN OPTIMALLY SCHEDULING DEPOT-LEVEL REPAIR ACTIVITY FOR THE UNITED STATES MARINE CORPS

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ABSTRACT

The United States Marine Corps' ability to wage war and its warfighting effectiveness rely heavily on the availability of its tactical ground equipment. The Marine Corps optimizes the warfighting availability of its tactical ground equipment in its depot-level repair plan, which commits $450 million over a six-year horizon. Currently, small changes (for example, budget) to the input to this model produce non-intuitive revisions that are needlessly disruptive. The Marine Corps Materiel Command (MATCOM) recognizes this problem and has asked for enhancement of their current model to include persistent features. We show that turbulence can be reduced at little cost in warfighting availability. We also investigate an approximate, but very fast heuristic in lieu of mathematical optimization to solve this problem. A simple greedy myopic heuristic quickly produces nearly-optimal advice to the depot-level planning problem.

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EXECUTIVE SUMMARY

The United States Marine Corps maximizes the warfighting availability of its tactical ground equipment through depot-level repair activity. The system that plans such activities currently produces too many expensive revisions after the Marine Corps publishes a maintenance plan and subsequent small input changes arise. The Marine Corps Materiel Command (MATCOM) recognizes this problem and has asked for enhancement to correct it. We suggest several changes to the current model to minimize the number of changes to an already-published legacy plan and investigate an approximate heuristic in lieu of optimization to solve this problem. Our simple myopic heuristic quickly produces nearly optimal advice for the depot-level planning problem without the requirement of expensive optimization software.

Currently, the Marine Corps uses the Dynamic Equipment Repair Optimization (DERO) model, an integer linear program, to suggest a maintenance plan. DERO optimizes multi-year, depot-level maintenance plans that maximize the aggregate value of available equipment while ensuring that an adequate number of each type asset is available when needed and that annual budget limits are observed. DERO has been used since 1998 to develop the Program Objective Memorandum (POM), which ultimately determines the overall depot-level funding for the Marine Corps.

The depot-level managers encounter a problem when they incorporate updated budget information into DERO. Budget projections for depot-level maintenance fluctuate regularly. Additional maintenance funds are granted, or, perhaps more likely, funds are rescinded in order to support other Marine Corps programs.

When the budget projection changes and DERO incorporates this change, a revised maintenance plan can be significantly different from the already-published legacy plan. These non-intuitive inconsistencies necessitate major revisions to already-published legacy plans.

We suggest some modifications to DERO to ensure that legacy plans are not revised needlessly. By incorporating a published legacy plan as input to the model, we encourage a revision to remain close to the legacy plan by penalizing deviations from the legacy plan. Our results show the effectiveness of these enhancements to DERO, improving the face validity of plans. We also show how restricting plans to retain legacy features affects the overall warfighting readiness of a revised maintenance plan.

In its current form, DERO requires someone experienced in modeling and an algebraic modeling language to understand and implement the changes we suggest. DERO also requires an expensive Generalized Algebraic Modeling System (GAMS) CPLEX™ integer linear programming solver to generate its proposed maintenance plan.

We provide a heuristic planning tool that is easy to use and can alleviate the above limitations. Our heuristic is implemented with EXCEL™ and uses Visual Basic to solve the depot-level planning problem. We show that this tool works on a simplified planning problem and can be trusted. Our myopic heuristic quickly solves the DERO planning problem and produces a suggested maintenance plan with the approximate warfighting readiness of formally optimized DERO.

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LIST OF ACRONYMS

BRACAS	Base Realignment and Closure Action Scheduler
CutS	Cutter Scheduler
DERO	Dynamic Equipment Repair Optimization Model
DLMP	Depot Level Maintenance Program
FY	Fiscal Year
GAMS	Generalized Algebraic Modeling System
IROAN	Inspect and Repair Only As Necessary
MATCOM	Marine Corps Materiel Command, Albany, GA
MCCDC	Marine Corps Combat Development Command, Quantico, VA
NRFI	Not Ready For Issue
POM	Program Objective Memorandum
RFI	Ready For Issue
TAMCN	Table of Authorized Material Control Number

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I. INTRODUCTION

A. DEPOT-LEVEL MAINTENANCE PLANNING

The United States Marine Corps' ability to wage war and its warfighting effectiveness rely heavily on the availability of its tactical ground equipment. However, maintenance funding for ground depots regularly falls short of the full amount required to overhaul all of the unserviceable equipment. Therefore, the Marine Corps must prioritize its depot-level funding to ensure the proper mix of equipment is available for its warfighters.

In the past, the Depot Level Maintenance Program (DLMP) program manager manually prioritized all of the end items in the Marine Corps ground inventory requiring depot-level maintenance. Regular maintenance conferences reviewed a rotation schedule, which plans for the modification, overhaul, and/or service life extension of each item in a fleet of equipment exactly once during a planning horizon [MATCOM, 2002a]. Other considerations include procurements, modification plans, estimates of unserviceable returns to the depots, and current and expected operational requirements.

A team of maintenance experts was responsible for assimilating this information and prioritizing the hundreds of items competing for limited repair resources. After a period of several weeks, this team eventually decided on a subset of items to fund. While this provided prioritizing, it often left many unfunded items in a critically short posture.

In order to correct this planning deficiency, the Marine Corps developed the Dynamic Equipment Repair Optimization (DERO) model. This model optimizes yearly depot-level maintenance activities across a six-year planning horizon while adhering to annual budget constraints. This model will be described in Chapter II.

Since 1998, the United States Marine Corps Material Command (MATCOM) has used this model to prepare its Program Objective Memorandum (POM) and plan its depot-level maintenance. Depot managers closely follow DERO's suggested maintenance plan for the first fiscal year or two in the planning horizon and incorporate it into their final maintenance plan.

B. DEALING WITH CHANGES

The depot-level managers encounter a problem when they incorporate updated budget information into DERO. Budget projections for depot-level maintenance fluctuate regularly. Additional maintenance funds are granted, or, perhaps more likely, funds are rescinded in order to support other Marine Corps programs.

When a budget projection changes and DERO incorporates this change, the new revised maintenance plan can be significantly different from a legacy plan. These non-intuitive inconsistencies between suggested plans can result in major revisions to an already-published legacy plan.

Unfortunately, mathematical programs have a well-deserved reputation for amplifying small input changes into significantly different solutions. An optimized plan that retains many of the features of an already-published legacy plan is much more managerially acceptable.

C. A SOLUTION FOR A PERSISTENCE PROBLEM

Brown, Dell, and Wood [1991] observe persistence problems in real-world applications when using optimization-based decision support and suggest several ways of mitigating the amount of turbulence between solutions. They describe how to encourage a revised optimal solution to retain features of a legacy optimal solution and define this idea as “persistence” between solutions. Using the techniques described in their article, we demonstrate how to incorporate persistence in DERO and show its effectiveness when using this new formulation with typical budget changes.

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II. RELATED RESEARCH

A. LITERATURE ON PERSISTENCE

Much of the literature on optimization describes theory and models of mathematical programming. The design and initial prototypic application of an optimization model takes precedence in publications. On the other hand, continued real world use of these models receives little attention.

Brown, Dell, and Wood [1991] explain the lack of attention to persistence with the following reasons:

1. Most papers tend to discuss new applications but persistent problems arise only after a model has been used for some time. This was the case with DERO.

2. Modelers tend to write papers. Therefore, they tend to focus on theoretical issues and ways to obtain optimal solutions.

3. Everyone deals with persistence in some way, but nobody admits it. Most modelers end up fixing variables and no one is proud of this sort of workaround.

They illustrate various methods of incorporating persistence through a series of case studies.

B. CASE STUDIES

Brown, Dell and Wood [1991] describe the following case studies in order to show optimization models that have exhibited persistence problems and some of the methods used to encourage persistence:

1. Scheduling Coast Guard Cutters

The First United States Coast Guard District uses Cutter Scheduler (CutS) to assign 16 cutters to weekly patrols, maintenance and training assignments over three months while minimizing total transit time. When changes arise in, for instance, the availability of a cutter, persistent solutions appeal when revising an already-published legacy schedule.

Each binary assignment variable in this model is encouraged to retain the value it had in a previous solution. The legacy value of each decision variable is converted into an elastic persistent variable. Each persistent variable has a target value that it is encouraged to obtain and a linear penalty for any deviation from that target. By using these elastic persistent variables, the authors show how changes to a revised quarterly schedule are reduced from 52 major changes to only 11.

2. Base Realignment and Closure Action Scheduler

The United States Army uses an integer linear program called Base Realignment and Closure Action Scheduler (BRACAS) to assist it in closing and realigning missions for military installations. This model maximizes the expected net present value of savings that the Army receives by scheduling closures and realignments across six years.

In this case, ranged persistent constraints were used to provide upper and lower limits for each of four budget categories. After publishing a legacy solution the prior year, the Army was able to incorporate improved schedule revisions and produce an acceptable plan that addressed these revisions while staying within the specified acceptable persistent ranges. Congress eventually approved this model’s revised plan.

3. Hamming Distance and Submarines

Another case study describes a model that produces an optimal berthing plan for submarines. By calculating a measure of the difference between solutions called the Hamming distance, the authors show how to incorporate a persistent incentive in the objective function. Their results show an effective way to reduce the amount of arbitrary and non-intuitive turbulence between legacy and revised berthing plans.

Using the techniques described in these three case studies, we will demonstrate how to incorporate persistence in the DERO model. Our results will show the effectiveness of persistence after typical budget changes to DERO’s input.

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III. DYNAMIC EQUIPMENT REPAIR OPTIMIZATION MODEL (DERO)

A. OVERVIEW

The Dynamic Equipment Repair Optimization model optimizes multi-year, depot-level maintenance plans that maximize the aggregate value of available equipment while ensuring that an adequate number of each type asset is available when needed and that annual budget limits are observed. DERO has been used since 1998 to develop the Program Objective Memorandum (POM), which ultimately determines the overall depot-level funding for the Marine Corps.

DERO consists of two distinct models: the Rotations model and the Readiness model, each addressing a different aspect of depot-level maintenance [Goodhart, 1999]. The Rotations model produces a depot-level maintenance plan for equipment designated as a rotation program. The Readiness model allocates the remaining resources on Inspect-and-Repair-Only-As-Necessary (IROAN) and other programs.

DERO first solves the Rotations model because rotations programs receive a higher priority. This model maximizes the smallest single-year budget surplus across the time horizon of interest for all rotations programs. The Readiness model maximizes the resulting availability of ground equipment with the remaining resources.

B. THE ROTATIONS MODEL

1. Rotations Model Description

A rotations program is one that calls for the modification, overhaul, and/or service life extension of each item in a fleet of equipment exactly once during the six-year planning horizon. The Rotations model is an integer linear program that determines the arrangement of multiple “once only” rotations programs that maximizes the smallest single-year, single-appropriation funding surplus across the specified planning horizon.

The Rotations model takes as input a set of possible starting years and a set of possible ending years for a subset of all of the Table of Authorized Materiel Control Numbers (TAMCNs). The model’s input also includes the minimum and maximum number that can be repaired for each TAMCN in this subset during each year. This integer program then finds the optimal combination of starting and ending years as well as the annual number to repair for this subset of TAMCNs within the yearly budget constraints.

2. Rotations Model Formulation

The Rotations model is as follows:

Indices:

f Forces (appropriations): ACTIVE or RESERVE,

t Table of Authorized Materiel control number (TAMCN) (equipment type), e.g. D0209,

v Possible years in which a rotation program could start,

w Possible years in which a rotation program could end,

y Years in the decision horizon (e.g. 2002, 2003, 2004, …);

Sets:

T TAMCNs *t*,

R Subset of *T*, TAMCNs required to undergo a rotation – e.g., *R* = {Axxxx},

V_t Possible starting years for TAMCN *t* rotation $(t \in R)$ -- e.g. Axxxx could start in 2002 or 2003,

W_t Possible ending years for TAMCN *t* rotation $(t \in R)$ -- e.g. Axxx could end in 2004 or 2005,

VW_t Set of possible rotation start-end year pairs for TAMCN *t*, $\{(v,w): v \in V_t, w \in W_t\}$, for example,

for TAMCN Axxxx above, VW_{Axxxx} = {(2002, 2004), (2002, 2005), (2003, 2004), (2003, 2005)}. Each of these pairs represents the time during which a rotation program could be funded,

$VW_{t,y}$ Possible TAMCN *t* start-end year pairs including year *y*, i.e., $\{(v,w) \in VW_t : v \le y \le w\}$, for example, $VW_{Axxxx,2005}$ = {(2002, 2005), (2003, 2005)};

Data:

$\underline{m}_{t,f}, \overline{m}_{t,f}$ Minimum and maximum number of TAMCN $t \in R$ assets that can or must be rotated from force *f* in any year,

$budget_{f,y}$ Funding available to force *f* in year *y*,

$q_{t,f}$ Total quantity of TAMCN *t* assets required for rotation for *f* over all years,

$rcost_t$ Cost per asset of TAMCN *t* in rotation in dollars;

Variables:

$DELTA_{f,y}$ Dollar amount that force *f* has left over from its budget in year *y*, after paying for all rotated assets; if negative, force *f* is over-budget;

$RB_{t,f,y}$ Number of TAMCN *t* assets funded by *f* for rotation in year *y*,

$P_{t,v,w}$ Binary variable, which is set to 1 if TAMCN *t* rotation starts in year *v* and ends in year *w*, 0 otherwise,

Z Maximum number of dollars saved after paying for all rotations, by any force in any year (possible negative if over-budget);

Formulation:

$$\text{Maximize } Z \qquad [1]$$

Subject to

$$\sum_t rcost_t RB_{t,f,y} + DELTA_{f,y} = budget_{f,y} \qquad \forall f, y \qquad [2]$$

$$Z \leq DELTA_{f,y} \qquad \forall f, y \qquad [3]$$

$$\sum_{(v,w)\in VW_{t,y}} \underline{m}_{t,f} P_{t,v,w} \leq RB_{t,f,y} \leq \sum_{(v,w)\in VW_{t,y}} \overline{m}_{t,f} P_{t,v,w} \qquad \forall\ t \in R, f, y \qquad [4]$$

$$\sum_{y} RB_{t,f,y} = q_{t,f} \qquad \forall\ t \in R, f \qquad [5]$$

$$\sum_{(v,w)\in VW_t} P_{t,v,w} = 1 \qquad \forall\ t \in R \qquad [6]$$

$$RB_{t,f,y} \in \{0,1,2,...\} \qquad \forall t \in R, f, y \qquad [7]$$

$$P_{t,v,w} \in \{0,1\} \qquad \forall t \in R, v, w \qquad [8]$$

3. Verbal Formulation

The objective function [1] expresses the smallest single-year budget surplus across the time horizon of interest.

Constraints:

[2] Each budget constraint ensures that the funding spent on rotations programs plus DELTA equals the budget limit for each force and year.

[3] Combined with the objective function, each constraint encourages the annual savings to be as large as possible.

[4] Each constraint requires that quantities funded for any TAMCN are between the minimum and maximum allowed and only occur during the period the program is scheduled.

[5] Each constraint requires that the total quantity funded for each TAMCN equals the quantity required for that force.

[6] Each constraint ensures that each TAMCN has only one starting and ending year.

[7] An integer decision is required.

[8] A binary decision is required.

C. THE READINESS MODEL

1. Readiness Model Description

The Readiness model incorporates a plan from the Rotations model and maximizes the resulting availability of ground equipment with the remaining resources. This model uses a readiness score to represent the availability of each TAMCN. Using this readiness measure, the model maximizes a weighted sum of the readiness scores of all TAMCNs.

In this model, each TAMCN is assigned a war material requirement, which represents the total number of assets authorized to all Marine Corps organizations and in sustainment stocks. The availability of a TAMCN in a given year is determined by using a ratio of the number of Ready-For-Issue (RFI) assets to its war material requirement. This ratio is referred to as an E-rating.

The Readiness model uses a piecewise linear function of an E-rating to determine a readiness score for each TAMCN. The higher the score, the better the readiness for that TAMCN. Negative scores represent TAMCNs with ratio of less than 0.7, and the Readiness model penalizes these. This readiness score for each TAMCN is an important part of the model’s objective function. Figure 1 shows how the score is calculated.

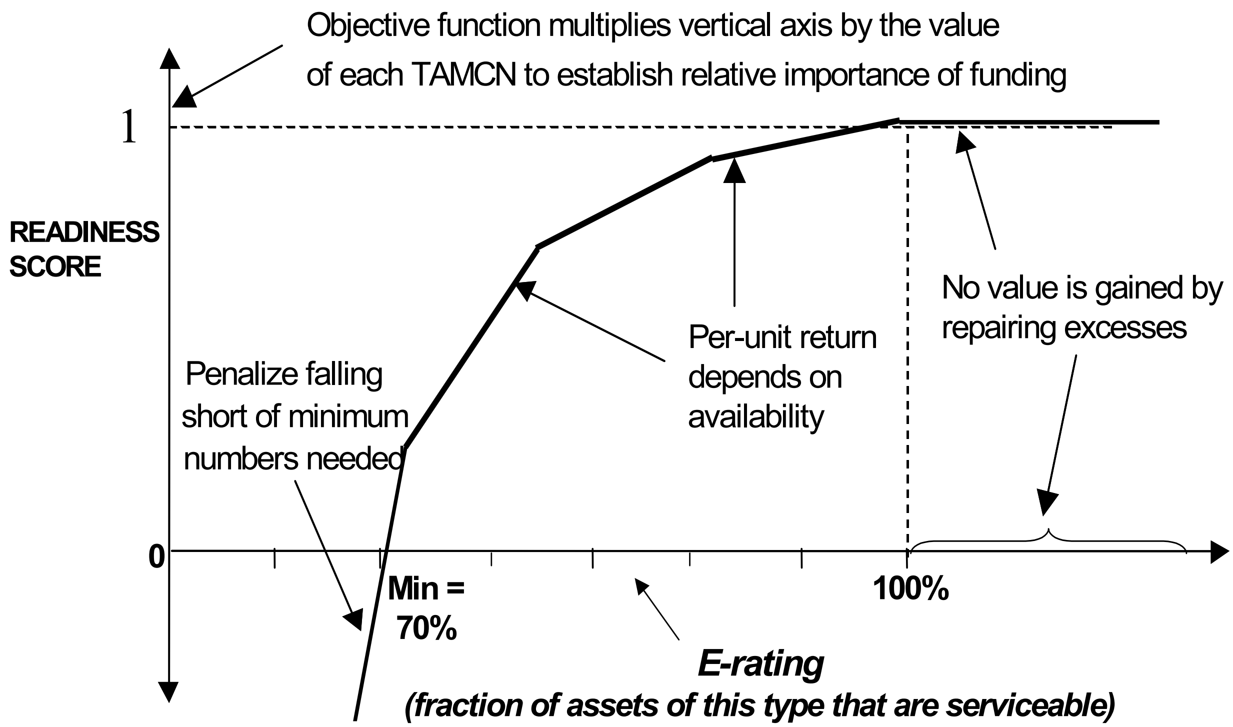

Figure 1. Maximizing a Readiness Score. The objective function uses the score for a given TAMCN to represent its warfighting readiness. The score is calculated by using a piecewise linear function similar to the one shown here.

The other important aspect of this model's objective function is the warfighting value of each TAMCN, representing the relative importance (or weighted importance) of that TAMCN as compared to other TAMCNs. The objective function expresses the sum of the readiness score of each TAMCN multiplied by its warfighting value.

In order to keep track of RFI and Not-Ready-For-Issue (NRFI) equipment quantities each year, a flow structure similar to the one in Figure 2 is employed. The RFI quantity for a TAMCN is increased by either repairing some of its NRFI assets in the depot or by the addition of newly issued items. RFI quantities decrease according to the estimated number of failures (or returns) each year.

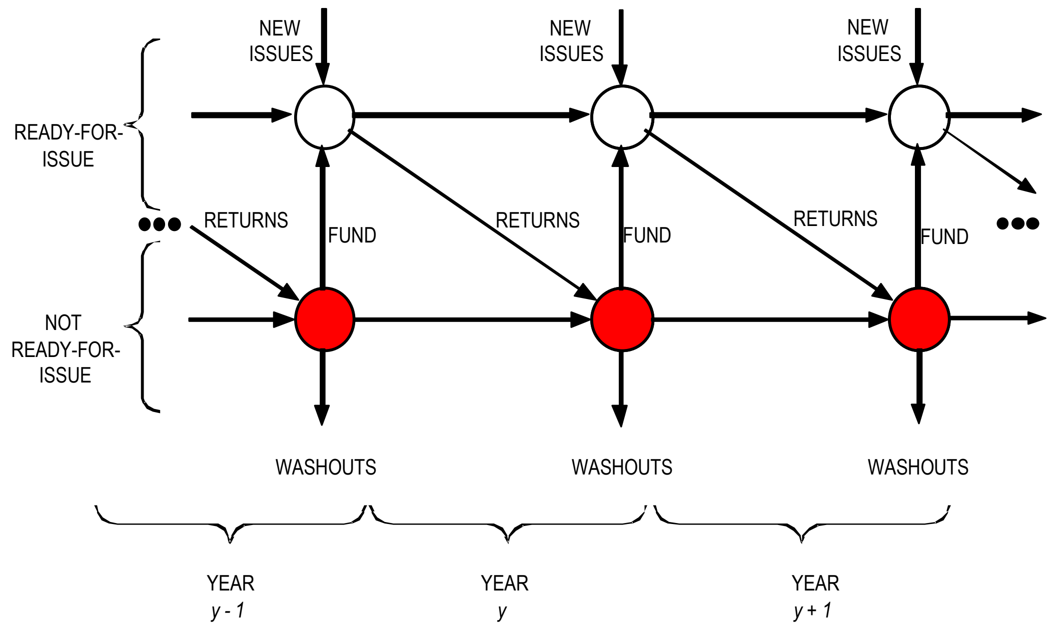

Figure 2. RFI and NRFI flow in the Readiness Model.
Quantities of new issues and unserviceable returns are the inputs for the model. Each vertical arrow labeled FUND corresponds to a decision variable in the model and incurs a specific cost for repairing each TAMCN.

The Readiness model is solved as an integer linear program for the first three years. The model relaxes integer requirements in later years. For a more detailed description of this model, see Goodhart [1999].

2. Readiness Model Formulation

The Readiness model is as follows:

Indices:

f Forces (appropriations): ACTIVE or RESERVE,

s Line segments bounding the objective function,

t Table of Authorized Materiel Control Number (TAMCN) (equipment type),

v Possible year in which a rotation program could start,

w Possible years in which a rotation program could end,

y Years in the decision horizon (e.g. 2002, 2003,…);

Sets:

C TAMCNs in "screening programs" funded by depot-maintenance accounts, or lump-sum payments denoted by unique TAMCNs indicating mandatory payment of a particular amount by these accounts,

R Subset of T, TAMCNs required to undergo a rotation,

T TAMCNs t,

$VW_{t,y}$ Possible TAMCN t start-end year pairs including year y, i.e., $\{(v,w) \in VW_t : v \le y \le w\}$;

Data:

β Discount factor to emphasize near-term years $(\beta < 1)$,

$budget_{f,y}$	Funding available to force *f* in year *y*,
$dspare0_t$	Starting number of unstratified (excess) NRFI assets of TAMCN *t*,
$icost_t$	Cost for “inspect and repair only as necessary” (IROAN) per asset of TAMCN *t*,
$intcpt_s$	Vertical intercept of segment *s*, in warfighting readiness units,
$issue_{t,y}$	Number of TAMCN *t* assets newly procured in year *y*,
pen_t	Per-asset shortage cost for failing to meet *rtgt* (readiness target) for TAMCN *t*,
$pen2_t$	Per-unit (elastic) penalty for adjusting initial RFI quantity,
$rcost_t$	Cost per asset of TAMCN *t* in rotation (rebuild, modification, SLEP etc.),
$rtgt_{t,f,y}$	Target availability percentage of TAMCN *t* at force *f* in year *y*,
$sbl_{t,f}$	Starting number of not-ready-for-issue (NRFI) assets of TAMCN *t* at force *f*,
$slope_s$	Slope of segment *s* in warfighting readiness units per E-rating,
$srfi_{t,f}$	Starting number of RFI assets of TAMCN *t* at force *f*,

$tilim_{t,f,y}$ Upper bound on number of turn-ins of TAMCN *t* from *f* in *y*,

$uspare0_t$ Starting number of unstratified (excess) RFI assets of TAMCN *t*,

$usr_{t,f,y}$ Unserviceable returns of *t* from *f* in *y*, exclusive of specific assets demanded for rotation,

$value_t$ Warfighting value of TAMCN *t* as determined by CG, MCCDC (S&A Division),

$wmr_{t,f,y}$ War materiel requirement of *t* at *f* in *y*,

y_o First year in decision horizon;

Fixed variables (optimal values determined by *Rotations* and used here as data):

$RB^*_{t,f,y}$ Number of TAMCN *t* assets funded by *f* for rotation in year *y*,

$P^*_{t,v,w}$ Binary variables set to 1 if TAMCN *t* rotation starts in year *v* and ends in year *w*, 0 otherwise,

Variables:

$CHEAT_{t,f}$ Nonexistent TAMCN *t* assets stratified to *f* at beginning of horizon to account for poor forecasting,

$DEFIND_{t,f,y}$ Binary variables set if *f* is short of its allowance (wmr) of *t* at end of *y*,

$FLOAT_{t,f,y}$ Quantity of RFI assets of *t* stratified to *f* in *y* (new or formerly excess),

$ISNRFI_{t,y}$ In-stores (depot) NRFI quantity of *t* and end of year *y*,

$ISRFI_{t,y}$ In-stores (depot) RFI quantity of *t* at end of year *y*,

$NRFI_{t,f,y}$ Quantity of TAMCN *t* NRFI assets stratified to *f* at end of year *y*,

$RC_{t,f,y}$ Quantity of TAMCN *t* RFI assets recalled for rotation from *f* at beginning of *y*,

$RFI_{t,f,y}$ Quantity of TAMCN *t* RFI assets stratified to *f* at end of year *y*,

$RPR_{t,f,y}$ Quantity of TAMCN *t* assets funded under IROAN for *f* in *y*,

$SCORE_{t,f,y}$ Readiness score of TAMCN *t* for *f* in *y*,

$SHORT_{t,f,y}$ Shortfall of TAMCN *t* RFI assets stratified to *f* at end of *y* with respect to availability target,

$STRN_{t,f,y}$ Quantity of NRFI TAMCN *t* assets re-stratified to *f* in *y* (paper-redistributed excess NRFI),

$TEDEF_{t,f,y}$ Difference between $wmr_{t,f,y}$ and quantity of *t* stratified to *f* at end of *y* (in any condition),

$TIS_{t,f,y}$ Quantity of TAMCN *t* RFI assets removed from stratification to *f* in *y*,

$TIU_{t,f,y}$ Quantity of TAMCN *t* NRFI assets removed from stratification to *f* in *y* without being repaired;

Formulation:

Maximize

$$\sum_{t,f,y} \beta^{y-y_0} value_t (SCORE_{t,f,y} - pen_t SHORT_{t,f,y}) - \sum_{t,f} pen2_t CHEAT_{t,f} \qquad [1]$$

Subject to

$$\sum_{t \notin R} icost_t RPR_{t,f,y} + \sum_{t \in R} rcost_t RB^*_{t,f,y} \le budget_{f,y} \qquad \forall f,y \qquad [2]$$

$$SCORE_{t,f,y} \le intcpt_s + slope_s \frac{RFI_{t,f,y}}{wmr_{t,f,y}} \qquad \forall s,t \notin C, f, y \qquad [3]$$

$$INSRFI_{t,y} = dspare0_t + \sum_f TIU_{t,f,y} - \sum_f STRN_{t,f,y} \qquad \forall t \notin C, y = y_0 \qquad [4]$$

$$ISNRFI_{t,y} = ISNRFI_{t,y-1} + \sum_f TIU_{t,f,y} - \sum_f STRN_{t,f,y} \qquad \forall t \notin C, y > y_0 \qquad [5]$$

$$ISRFI_{t,y} = uspare0_t + issue_{t,y} - \sum_f FLOAT_{t,f,y} + \sum_f TIS_{t,f,y} \qquad \forall t \notin C, y = y_0 \qquad [6]$$

$$ISRFI_{t,y} = ISRFI_{t,y-1} + issue_{t,y} - \sum_f FLOAT_{t,f,y} + \sum_f TIS_{t,f,y} \qquad \forall t \notin C, y > y_0 \qquad [7]$$

$$NRFI_{t,f,y} = \begin{cases} sbl_{t,f} + usr_{t,f,y}\left(1 - \sum_{(v,w)\in VW_{t,y}} P^*_{t,v,w}\right) + RC_{t,f,y} \\ -RB_{t,f,y} - RPR_{t,f,y} - TIU_{t,f,y} + STRN_{t,f,y} \end{cases}$$

$$\forall t \notin C, f, y = y_0 \qquad [8]$$

$$NRFI_{t,f,y} = \begin{cases} NRFI_{t,f,y-1} + usr_{t,f,y}\left(1 - \sum_{(v,w)\in VW_{t,y}} P^*_{t,v,w}\right) + RC_{t,f,y} \\ \quad -RB_{t,f,y} - RPR_{t,f,y} - TIU_{t,f,y} + STRN_{t,f,y} \end{cases}$$

$$\forall\ t \notin C, f, y > y_0 \quad [9]$$

$$RFI_{t,f,y} = \begin{cases} srfi_{t,f} + CHEAT_{t,f} - usr_{t,f,y}\left(1 - \sum_{(v,w)\in VW_{t,y}} P^*_{t,v,w}\right) \\ -RC_{t,f,y} + RB_{t,f,y} + RPR_{t,f,y} - TIS_{t,f,y} + FLOAT_{t,f,y} \end{cases}$$

$$\forall\ t \notin C, f, y = y_0 \quad [10]$$

$$RFI_{t,f,y} = \begin{cases} RPR_{t,f,y} + CHEAT_{t,f} - usr_{t,f,y}\left(1 - \sum_{(v,w)\in VW_{t,y}} P^*_{t,v,w}\right) \\ -RC_{t,f,y} + RB_{t,f,y} + RPR_{t,f,y} - TIS_{t,f,y} + FLOAT_{t,f,y} \end{cases}$$

$$\forall\ t \notin C, f, y > y_0 \quad [11]$$

$$RFI_{t,f,y} \geq rtgt_{t,f,y} wmr_{t,f,y} - SHORT_{t,f,y} \qquad \forall\ t \notin C, f, y \quad [12]$$

$$TEDEF_{t,f,y} \leq DEFIND_{t,f,y} wmr_{t,f,y} \qquad \forall\ t \notin C, f, y \quad [13]$$

$$TIU_{t,f,y} + TIS_{t,f,y} \leq (1 - DEFIND_{t,f,y}) tilim_{t,f,y} \qquad \forall\ t \notin C, f, y \quad [14]$$

$$NRFI_{t,f,y} + RFI_{t,f,y} + TEDEF_{t,f,y} \geq wmr_{t,f,y} \qquad \forall\ t \notin C, f, y \quad [15]$$

$$RPR_{t,f,y} \leq usr_{t,f,y}\left(1 - \sum_{(v,w)\in VW_{t,y}} P^*_{t,v,w}\right) \qquad \forall\ t, y \quad [16]$$

$$RC_{t,f,y} \leq RB^*_{t,f,y} \qquad \forall\ t \in R, f, y \quad [17]$$

$$RPR_{t,f,y} = usr_{t,f,y} \qquad \forall\ t \in C, f, y \quad [18]$$

$$SCORE_{t,f,y} \leq 1 \qquad \forall\ t, f, y \quad [19]$$

$$RPR_{t,f,y} \in \{0,1,2,...\} \qquad \forall\ t, f, y \quad [20]$$

$$DEFINED_{t,f,y} \in \{0,1\} \qquad \forall\ t, f, y \quad [21]$$

$$FLOAT_{t,f,y}, NRFI_{t,f,y}, RC_{t,f,y}, RFI_{t,f,y} \geq 0 \qquad \forall\ t,f,y \qquad [22]$$

$$SHORT_{t,f,y}, STRN_{t,f,y}, TEDEF_{t,f,y}, TIS_{t,f,y}, TIU_{t,f,y} \geq 0 \qquad \forall\ t,f,y \qquad [23]$$

$$CHEAT_{t,f} \geq 0 \qquad \forall\ t,f \qquad [24]$$

$$ISRFI_{t,y} \geq 0 \qquad \forall\ t,y \qquad [25]$$

3. Verbal Formulation

The objective function [1] expresses the weighted sum of the readiness score less penalties associated with failing to meet the target availability.

Constraints:

[2] Each budget constraint ensures budget limits are respected for each force and year.

[3] Each constraint calculates the readiness score for each TAMCN.

[4-5] When combined, these constraints keep track of in-stores NRFI assets across planning years.

[6-7] When combined, these constraints keep track of in-stores RFI assets across planning years.

[8-9] When combined, these constraints keep track of stratified NRFI assets over planning years.

[10-11] When combined, these constraints keep track of stratified RFI assets over planning years.

[12] Each elastic constraint is used to encourage minimum readiness; each shortfall (SHORT) is penalized in the objective function.

[13-15] Together, these constraints prevent arbitrary redistribution of assets.

[16] Each constraint limits the number of assets funded for repair to be less than or equal to the number of unserviceable returns.

[17] Each constraint provides an upper bound on assets that can be recalled.

[18] Each constraint ensures that screening programs are funded.

[19] Each constraint provides an upper bound on the readiness score.

[20] An integer decision is required.

[21] A binary decision is required.

[22-25] A non-negative decision is required.

IV. TURBULENCE BETWEEN LEGACY PLANS AND REVISIONS

A. USING DERO TO PROVIDE A DEPOT-LEVEL MAINTENANCE PLAN

The typical use of DERO to provide a maintenance plan is summarized with the following steps:

1. All of the input is gathered.
2. DERO is solved.
3. The solution is published as the maintenance plan.
4. Revised information becomes available and is incorporated into DERO. Typically, this is updated budget information.
5. With this updated information, return to Step 2.

A revised maintenance plan often varies greatly from an already-published legacy plan. The depot-level planners complain that a revised maintenance plan is too different from a legacy plan. This non-intuitive inconsistency between legacy and revised plans results in major revisions to the already-published legacy plan. Ultimately, DERO could lose its credibility to produce an optimal maintenance plan for its users.

B. MAJOR AND MINOR CHANGES

Changes between solutions are categorized here as major changes and minor changes. A major change is the complete cancellation of a published repair program or the suggested start-up of a new program in a given fiscal year for a given TAMCN. A minor change occurs when the number of assets to be repaired changes within a fiscal year for a

TAMCN, but the TAMCN is neither completely cancelled nor suggested for a new start-up.

C. ILLUSTRATING TURBULENCE AFTER A BUDGET CHANGE

We solve DERO with an original data set [MATCOM, 2002b]. The projected budgets for the active forces are as follows:

Year	Budget (millions)
2002	$105.6 (Reduced to $104.1)
2003	$109.9
2004	$73.3
2005	$75.9
2006	$76.7
2007	$78.1

Table 1. An original (and revised) budget projection. After publishing an original maintenance plan, depot managers must revise plans due to a $1.5 million budget reduction in FY2002.

The budget reduction in Table 1 reflects a 1.4% decrease in the first fiscal year of this six-year set and is the only change to the input data. When we compare the legacy plan to the revised plan, we realize that DERO suggests a revision that requires 20 major changes and 36 minor changes to the already-published legacy maintenance plan. The changes to the legacy plan are shown in Table 2.

TAMCN	2002	2003	2004	2005	2006	2007
A0010						
A0043		-3	-3			
A0966						
A1260	-1		1			
A1440						
A1500						
A1503						
A1530						
A2306						
A2635	-1					
A7005	-1					
A7025						
A7035						
A7037						
A7052						
A7055	-4					
A7058						
A7072						
A7500						
A7590						
B0001						
B0114	-1					1
B0395						
B0443						
B0589			1	-0.9		

TAMCN	2002	2003	2004	2005	2006	2007
B0635		-2				2
B0730	-3	-36			0.3	38.7
B1082						
B1226						
B1298		-1				
B1315			-2		2	
B1580	-1					
B2464						
B2482						
B2685		-4				
C2032		-17				
D0080						
D0105						
D0209						
D0860	2			-1.9		
D0876						
D0877						
D0878						
D0879						
D0880	-82			54.2	27.8	
D1072						
D1134		1		-1		
D1212						
E0180			-11	11		

TAMCN	2002	2003	2004	2005	2006	2007
E0726						
E0727			1			
E0942						
E0946						
E0947						
E0948						
E0949						
E0950						
E0960	-8	-128	1	135		
E0961	-4					
E0980			-37	21.8	15.2	
E0998		-1	-20	21		
E1037						
E1251	-12		-2		14	
E1313						
E1441	-1	3	2	-4		
E1460						
E1475						
E1836						
E1888	-1	1		-0.93	-0.58	-0.69
E3196						
A0000						
E0000						
E0001						

Table 2. Turbulence in DERO after a typical budget reduction.

This table summarizes the TAMCNs that received funding in either the legacy or revised plan. Only changes are shown in this table. Positive numbers represent an increase in repairs for a given TAMCN in the revised plan while the negative numbers represent a decrease. TAMCNs without any changes noted remain the same in both legacy and revised plans. Major changes are indicated with shaded cells. For example, DERO suggested a major change to A7055 in FY2002 by reducing the number to be repaired from four to zero while B1315 had two minor changes in FY2004 and FY2006. On the other hand, A1503 remained unchanged between legacy and revised plans.

D. INCORPORATING PERSISTENCE

A revised maintenance plan that retains many of the features of an already-published legacy plan is clearly more managerially acceptable. By making DERO “remember” a legacy plan, we can encourage a revised plan to be less turbulent. This encouragement is what is meant by the term persistence.

1. Elastic Persistence for the Rotation and Repair Decision Variables

When using elastic persistent variables, each decision variable has a target value that it is encouraged to obtain. Typically, the target value of a decision variable is its value from a legacy plan. A linear penalty in the objective function can be used to discourage any deviation from the target value.

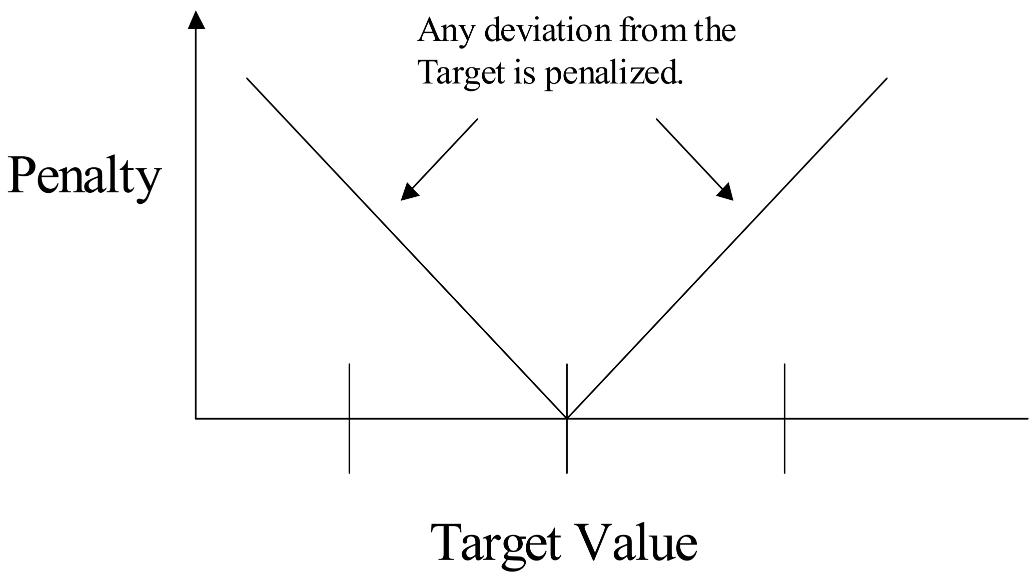

Figure 3. Illustrating an Elastic Persistent Variable.
Each decision variable is given a target value and any deviation from that value is penalized with a linear penalty.

We describe how to accomplish this in the Rotations model for the $RB_{t,f,y}$ decision variable, which represents the number to rotate of TAMCN t within force f in each year y within the specified starting and ending year.

The target value of each decision variable will be the value of that decision variable from the legacy plan. We incorporate these values as a parameter in a persistent Rotations model: $RBold_{t,f,y}$. This value is the target value for each TAMCN t within force f in year y in the revised plan.

Incorporating elastic persistent variables in linear programming requires measuring the absolute value of the difference between the legacy value of a decision variable and its revised value. Accomplishing the absolute value of a difference between two variables in linear programming requires the addition of two non-negative decision variables, e.g. $Pdiff_{t,f,y}$ and $Ndiff_{t,f,y}$. $Pdiff_{t,f,y}$ represents the positive difference between a revised and a legacy plan, $RBold_{t,f,y}$, while $Ndiff_{t,f,y}$ represents the absolute magnitude of the negative difference between these values.

Additions and changes to the Rotations model to incorporate persistence are as follows:

Added Parameters:

$RBold_{t,f,y}$	Rotation decision (RB) from a legacy plan,
$RBpenalty$	Linear penalty to encourage persistence in RB decision variables ($/change),

Added Positive Variables:

$Pdiff_{t,f,y}, Ndiff_{t,f,y}$	Positive and negative difference between legacy plans, $RBold_{t,f,y}$, and revision, $RB_{t,f,y}$;

New Objective Function:

Maximize $$Z - RBpenalty * \sum_{t,f,y} (Pdiff_{t,f,y} + Ndiff_{t,f,y}) \quad [1]$$

Additional Constraints:

$$Pdiff_{t,f,y} - Ndiff_{t,f,y} = RBold_{t,f,y} - RB_{t,f,y} \qquad \forall t \in R, f, y \quad [2]$$

$$Pdiff_{t,f,y}, Ndiff_{t,f,y} \geq 0 \qquad \forall t \in R, f, y \quad [3]$$

The new objective function [1] now includes a penalty for every change in decision variables between legacy and revised plans. Together, constraints [2] and [3] capture the change between legacy and revised plans for each decision variable.

We incorporate the same reformulation for the $RPR_{t,f,y}$ decision variable in the Readiness model.

2. Hamming Penalty for a Rotation Program's Starting and Ending Year

Hamming distance measures the number of corresponding bits that differ between two binary decision variables [Hamming, 1986]. By incorporating Hamming distance into the objective function, turbulence between representative binary decision variables can be mitigated. Brown, Dell, and Wood [1991] define this as a Hamming penalty. This penalty is implemented by incorporating an elastic persistent constraint that discourages any change between legacy and revised plans.

The Rotations model incorporates binary variables to indicate the starting year and ending year of a rotation program for a given TAMCN. Encouraging similar starting and ending years for each TAMCN between legacy and revised plans is another important aspect of the Rotations model requiring persistence. As before, we use a parameter to capture a legacy value, $Pold_{t,v,w}$, and use it as the target value for that decision variable in the revision.

An additional constraint is used to measure the Hamming distance between legacy and revised plans. A Hamming penalty is included in the objective function to reduce Hamming distance and thus encourage persistence in the Rotations model. The remaining additions and changes are as follows:

Additional Parameters:

$Pold_{t,v,w}$	Binary variables ($P_{t,v,w}$) from a legacy plan,
$Ppenalty$	Linear penalty to encourage persistence in P decision variables in revisions,

Additional Variable:

$Pchanges$	Number of changes between a revision, $P_{t,v,w}$, and legacy plan, $Pold_{t,v,w}$;

Final Objective Function:

Maximize

$$Z - Ppenalty * Pchanges - RBpenalty * \sum_{t,f,y} (Pdiff_{t,f,y} + Ndiff_{t,f,y}) \quad [1]$$

Additional Constraints:

$$\sum_{t,v,w|Pold_{t,v,w}=0} P_{t,v,w} + \sum_{t,v,w|Pold_{t,v,w}=1} (1 - P_{t,v,w}) = Pchanges \quad [2]$$

$$Pchanges \geq 0 \quad [3]$$

The final objective function [1] now includes a penalty for every change in each decision variable between a legacy and revised plan. Together, constraints [2] and [3] measure the Hamming distance between legacy and revised plans. This distance is penalized in the objective function.

3. Elastic (Ranged) Persistence for the Rotation and Repair Decision Variables

When using elastic (ranged) persistent variables, each decision variable has an interval that it is encouraged to obtain. This target interval for each decision variable will be based on its value from a legacy plan. A linear penalty in the objective function is used to discourage any deviation from the target value but only applies outside the target interval. Figure 4 helps illustrate this:

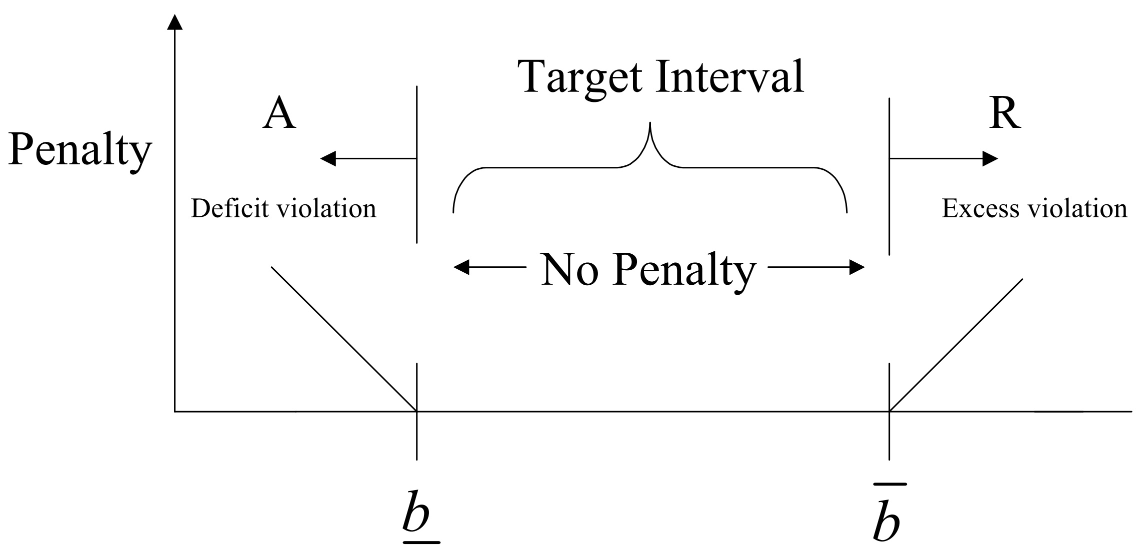

Figure 4. Illustrating a Ranged Persistent Variable.
Each decision variable has an upper limit ($\overline{b}$) and lower limit ($\underline{b}$) within which the decision variable can change without incurring any penalty. Positive values for *A* or *R* are assigned a linear penalty.

The upper and lower limit of each decision variable can vary by year based on a fraction of the target value. In this formulation, we seek to minimize the amount of turbulence between legacy and revised plans by providing acceptable regions for decision variables.

We describe how to accomplish this in the Rotations model. Decision variable, $RB_{t,f,y}$, represents the number to rotate of TAMCN t within force f in each year y. We use the value from each decision variable in a legacy plan ($RBold_{t,f,y}$) to provide the basis for the target interval for each decision variable. We use this legacy value to determine our upper limit ($\bar{b}$) and our lower limit ($\underline{b}$) as follows:

$$\bar{b}_{t,f,y} = (1+\alpha_y)\, RBold_{t,f,y}$$

$$\underline{b}_{t,f,y} = (1-\alpha_y)\, RBold_{t,f,y}$$

Here, α_y is the allowable fraction change to a decision variable in year y. An alternate method for defining the upper and lower limit for each decision variable is to add and subtract a fixed number from each decision variable. This could be handled as follows:

$$\bar{b}_{t,f,y} = RBold_{t,f,y} + k$$

$$\underline{b}_{t,f,y} = \max\left(0, RBold_{t,f,y} - k\right)$$

There are other possible ways to calculate a target interval, but we use fraction changes to decision variables in this thesis.

We incorporate persistence with the following additions to the Rotations model:

Added Parameters:

$RBold_{t,f,y}$	Rotation decision (RB) from a legacy plan,
$UpB_{t,f,y}, LoB_{t,f,y}$	$\overline{b}_{t,f,y}, \underline{b}_{t,f,y}$ as shown above,
$RBpenalty$	Linear penalty to encourage persistence in RB decision variables,

Added Positive Variables:

$A_{t,f,y}$	Difference penalized below lower limit $\underline{b}_{t,f,y}$,
$R_{t,f,y}$	Difference penalized above upper limit $\overline{b}_{t,f,y}$,
$S_{t,f,y}$	Difference allowed between upper and lower limits (target interval),
α_y	Allowable fraction change in year y,

New Objective Function:

Maximize

$$Z - RBpenalty * \sum_{t,f,y} (A_{t,f,y} + R_{t,f,y}) \qquad [1]$$

Additional Constraints:

$$RB_{t,f,y} + A_{t,f,y} - R_{t,f,y} + S_{t,f,y} = \overline{b}_{t,f,y} \qquad \forall t \in R, f, y \qquad [2]$$

$$S_{t,f,y} \leq \overline{b}_{t,f,y} - \underline{b}_{t,f,y} \qquad \forall t \in R, f, y \qquad [3]$$

The final objective function [1] now includes a financial penalty for every change outside the target interval. Together, constraints [2] and [3] measure any change outside the target interval between legacy and revised plans. This amount is penalized in the objective function.

In the Rotations model, we combine this formulation with Hamming penalties for the $P_{t,v,w}$ decision variable. We incorporate the same ranged elastic persistent reformulation for the $RPR_{t,f,y}$ decision variable in the Readiness model.

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V. PERSISTENT RESULTS

A. RESULTS USING ELASTIC PERSISTENT VARIABLES

Recall the original example used to illustrate turbulence between model solutions. We solved DERO with the following set of yearly budgets for the active forces:

Year	Budget (millions)
2002	$105.6 (Reduced to $104.1)
2003	$109.9
2004	$73.3
2005	$75.9
2006	$76.7
2007	$78.1

Table 3. A budget reduction with persistence. After publishing a maintenance plan, the FY2002 budget is reduced by $1.5 million. We can now use our persistent formulation of DERO to solve this revised problem.

Now, we test the new elastic persistent formulation. This new persistent formulation will produce a revised maintenance plan that linearly penalizes any change between a legacy and revised plan. In the Rotations model, we penalize exactly one dollar for each change. A change in the Readiness model, which maximizes a weighted sum of readiness scores, is penalized one unit of readiness. Table 4 displays the suggested revision produced by the non-persistent DERO model. The results using the persistent formulation are shown in Table 5.

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010							B0635		-2				2	E0726						
A0043		-3	-3				B0730	-3	-36			0.3	38.7	E0727			1			
A0966							B1082							E0942						
A1260	-1		1				B1226							E0946						
A1440							B1298		-1					E0947						
A1500							B1315			-2		2		E0948						
A1503							B1580	-1						E0949						
A1530							B2464							E0950						
A2306							B2482							E0960	-8	-128	1	135		
A2635	-1						B2685		-4					E0961	-4					
A7005	-1						C2032		-17					E0980			-37	21.8	15.2	
A7025							D0080							E0998		-1	-20	21		
A7035							D0105							E1037						
A7037							D0209							E1251	-12		-2		14	
A7052							D0860	2			-1.9			E1313						
A7055	-4						D0876							E1441	-1	3	2	-4		
A7058							D0877							E1460						
A7072							D0878							E1475						
A7500							D0879							E1836						
A7590							D0880	-82			54.2	27.8		E1888	-1	1		-0.93	-0.58	-0.69
B0001							D1072							E3196						
B0114	-1					1	D1134		1		-1			A0000						
B0395							D1212							E0000						
B0443							E0180			-11	11			E0001						
B0589			1	-0.9																

Table 4. Non-persistent results after a budget reduction.
Recall that, when the FY2002 budget was reduced from $105.6 to $104.1 million and resolved, these 56 (20 major and 36 minor) changes occurred.

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010							B0635							E0726						
A0043							B0730							E0727						
A0966							B1082							E0942						
A1260							B1226							E0946						
A1440							B1298							E0947						
A1500	-3			1	2		B1315							E0948						
A1503							B1580							E0949						
A1530							B2464							E0950						
A2306							B2482							E0960	-1			1		
A2635							B2685							E0961						
A7005							C2032							E0980						
A7025							D0080							E0998						
A7035							D0105							E1037	-1			1		
A7037	-1			1			D0209							E1251						
A7052							D0860							E1313						
A7055							D0876							E1441						
A7058							D0877							E1460						
A7072							D0878							E1475						
A7500							D0879							E1836						
A7590							D0880							E1888				-1.1	-1.5	
B0001							D1072							E3196	-2			2		
B0114							D1134							A0000						
B0395							D1212							E0000						
B0443							E0180							E0001						
B0589																				

Table 5. Persistent results after a budget reduction.
Much of the turbulence shown in Table 4 has disappeared using the added persistent features in DERO. This persistent revision suggests just 13 changes with only one of them being major.

Suppose that the 13 changes specified in Table 5 are still too many. We can then increase the linear penalty in order to further discourage turbulence between legacy and revised plans. Consider increasing the penalty in the following manner. In the Rotations model, we now penalize 1,000 dollars for each change. And changes in the Readiness model are penalized 1,000 units of readiness. In this case, the number of changes is further reduced from 13 down to 7. Table 6 summarizes the results below:

	2002	2003	2004	2005	2006	2007
A0010	-1					1
A0043						
A0966						
A1260						
A1440						
A1500	-1				1	
A1503						
A1530						
A2306						
A2635						
A7005						
A7025						
A7035						
A7037						
A7052						
A7055						
A7058						
A7072						
A7500						
A7590						
B0001						
B0114						
B0395						
B0443						
B0589						

	2002	2003	2004	2005	2006	2007
B0635						
B0730						
B1082						
B1226						
B1298						
B1315						
B1580						
B2464						
B2482						
B2685						
C2032						
D0080						
D0105						
D0209						
D0860						
D0876						
D0877						
D0878						
D0879						
D0880						
D1072						
D1134						
D1212						
E0180						

	2002	2003	2004	2005	2006	2007
E0726						
E0727						
E0942						
E0946						
E0947						
E0948						
E0949						
E0950						
E0960						
E0961						
E0980						
E0998						
E1037						
E1251						
E1313						
E1441						
E1460						
E1475						
E1836						
E1888	-1				-0.7	-0.8
E3196						
A0000						
E0000						
E0001						

Table 6. Increasing the persistence penalty. The number of changes is further reduced from 13 in Table 5 to just 7 changes by increasing the penalty from one objective function unit per change to one thousand. Increasing the penalty for changes is an effective way to reduce turbulence between legacy and revised plans.

Incorporating elastic persistent constraints into DERO is an effective way to reduce the amount of turbulence between plans when the input parameters are only slightly changed between legacy and revised plans. Also, the examples help illustrate how higher penalties can be used to encourage tighter persistence. Later, we explore how this reduction in turbulence affects the overall warfighting readiness of our revised plan.

B. RESULTS USING RANGED ELASTIC PERSISTENT VARIABLES

In this section, we incorporate the elastic (ranged) persistent model. Each decision variable now has an upper and lower limit of acceptable change based on a fraction of its value from a legacy plan. A linear penalty in the objective function is used to discourage any deviation outside this safe interval.

We solve DERO using ranged elastic persistent variables under the same conditions outlined in Table 3. In this example, we let $\alpha_y = 0.02$ for all *y* and calculate $\overline{b}$ and $\underline{b}$ as described in Chapter IV.

Outside the target interval, we penalize for change in the following manner. In the Rotations model, we penalize five dollars for each change. And changes in the Readiness model are penalized five units of readiness. The results of this formulation are as follows:

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010							B0635	-1					1	E0726						
A0043	-2		-2				B0730	-1					1	E0727						
A0966							B1082							E0942						
A1260			-1				B1226							E0946						
A1440							B1298							E0947						
A1500	-1				1		B1315			-1		1		E0948						
A1503							B1580							E0949						
A1530			-3				B2464							E0950						
A2306							B2482							E0960	-6			6		
A2635							B2685							E0961						
A7005							C2032	-3						E0980	-3		-2		5	
A7025							D0080							E0998	-3			3		
A7035							D0105							E1037						
A7037			-1	1			D0209	-3			3			E1251			-4		4	
A7052							D0860							E1313			-1			
A7055							D0876	1			-0.9			E1441						
A7058							D0877							E1460			-1			1
A7072							D0878							E1475				0.1	-0.1	
A7500							D0879							E1836						
A7590			1	-0.1	-0.3	-0.3	D0880	-2				2		E1888	-1		1	-0.7	-0.8	
B0001							D1072							E3196						
B0114							D1134							A0000						
B0395							D1212							E0000						
B0443							E0180	-1		-1	2			E0001						
B0589																				

Table 7. Elastic ranged persistence.

Clearly, there is more turbulence in this solution than we saw in the previous persistent model. In this case, the revised plan suggests 46 changes, one of which is major.

Major and minor changes between legacy and revised plans are defined as before. Because our targets are now intervals vice points, a revised plan using ranged elastic persistence can exhibit more turbulence due to our definitions of major and minor changes.

When the allowable change (α_y) equals zero, elastic ranged persistence reduces to elastic persistence. If allowing $\alpha_y = 0.02$ for all *y* produces a revised plan that is too turbulent, we instead let $\alpha_{2002} = 0$ and $\alpha_y = 0.02$ for all remaining *y*. In this case, we are penalizing linearly for any change in FY2002 and encouraging target intervals in the remaining years. Using the same penalties as before, the results are as follows:

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010	-1					1	B0635							E0180			-1	1		
A0043			-1				B0730							E0726						
A0966							B1082							E0727						
A1260			1				B1226							E0856						
A1440							B1298							E0942						
A1500	-3			1	2		B1315							E0946						
A1503							B1580							E0947						
A1530							B2085							E0948						
A2306							B2464							E0949						
A2635							B2482							E0950						
A7005							B2685							E0960						
A7025							C2032							E0961						
A7035							D0080							E0980			2		-2	
A7037							D0105							E0999						
A7052							D0209							E1037						
A7055							D0235							E1251						
A7058							D0860							E1313						
A7072							D0876							E1441						
A7500							D0877							E1460				-0.8		0.8
A7590							D0878							E1475				-0.2	0.2	
B0114							D0879							E1836						
B0395							D0880							E1888				-0.74	-1.47	-0.83
B0443							D1072							E3196						
B0446							D1134													
B0589							D1212													

Table 8. Improved ranged persistence.
This revised plan was obtained by linearly penalizing any change in the first year while allowing a two percent change in the remaining years. The revision exhibits 18 changes (two major) and represents a feasible alternative to the elastic persistent solution shown in Table 5.

Rather than following advice as strict as that produced by the elastic persistent model (shown in Table 5), this method can provide a decision-maker an alternate revised plan. In conjunction with the elastic persistent model, this can be a valuable tool.

C. USING PERSISTENT DERO WITH A BUDGET INCREASE

We have illustrated turbulence in DERO resulting from a budget reduction and have shown how to mitigate it using elastic persistent constraints. In this section, we explore how an increasing budget affects the amount of turbulence in DERO.

In this example, the projected budget changes according to the following table:

Year	Budget (millions)
2002	$105.6 (Increased to $109.6)
2003	$109.9
2004	$73.3
2005	$75.9
2006	$76.7
2007	$78.1

Table 9. An increasing budget example.
After publishing a maintenance plan, depot managers receive an additional $4 million for FY2002.

When this revision is made and solved by DERO, the suggested changes to the original plan are shown in Table 10. Because we are revising for a budget increase, revisions might better be restricted to augment legacy repairs or initiate new ones, rather than abandon any prior planned activity. This is a common sense consideration that might not be absolutely mathematically optimal.

If we modify the persistent DERO formulation so that we only penalize for negative changes to our decision variables between legacy and revised plans, we obtain the suggested changes to the legacy plan shown in Table 11. Clearly, the persistent DERO formulation can produce an acceptable revision under these conditions.

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010							B0589	1			-0.9			E0726						
A0043		-2	-3				B0635							E0727			5			
A0248	1						B0730		3				-0.3	E0856	1					
A0966							B1082							E0942						
A1260	1						B1226	2	-2					E0946						
A1440							B1298		7					E0947						
A1500							B1315			-2		2		E0948						
A1503							B1580	-1						E0949						
A1530							B2464							E0950						
A2306							B2482							E0960	15	277	1	-293		
A2635	-1						B2685							E0961	2					
A7005	6						C2032	-180	-36					E0980			18		-18	
A7025							D0080	77			-0.4	-56	-20.6	E0998			25	-1.8	-23.2	
A7035							D0105							E1037						
A7037							D0209							E1251						
A7052							D0235	1						E1313						
A7055	-1	3					D0860	203			-46	-46	-46	E1441	2	2		-4		
A7058							D0876							E1460		-1		-24.2		25.2
A7072			4				D0877							E1475				-7	6	12
A7500							D0878							E1836						
A7590							D0879							E1888	1	-1		2	0.5	-0.4
B0001							D0880	58				-30.2	-27.8	E3196						
B0114							D1072													
B0395		1	-1				D1134	1	1		-2									
B0443		-1	1				D1212													
B0446	1	1			12.7	14	E0180			6	-6									

Table 10. Turbulence following a revised, increased budget using DERO.
Just as we saw in the case of a budget reduction, non-persistent DERO exhibits a great deal of turbulence after a budget increase.

	2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007		2002	2003	2004	2005	2006	2007
A0010							B0635							E0180						
A0043							B0730							E0726						
A0966							B1082							E0727						
A1260							B1226							E0856	1					
A1440							B1298							E0942						
A1500							B1315							E0946						
A1503							B1580							E0947						
A1530							B2085	1						E0948						
A2306							B2464							E0949						
A2635							B2482							E0950						
A7005	6						B2685							E0960	15					
A7025							C2032							E0961						
A7035							D0080	103						E0980						
A7037							D0105							E0999	20					
A7052							D0209							E1037						
A7055							D0235	3						E1251						
A7058							D0860	239						E1313						
A7072							D0876							E1441	1					
A7500							D0877							E1460						
A7590							D0878							E1475						0.72
B0114							D0879							E1836						
B0395							D0880	59						E1888				0.23		
B0443							D1072							E3196						
B0446				0.7			D1134													
B0589	1			-0.9			D1212													

Table 11. An increasing budget using persistent DERO.
Without fixing any variables, we can use the persistent DERO formulation to show the optimal way to spend the additional $4 million in FY2002 without reducing any legacy repair activities.

D. WARFIGHTING READINESS AND TURBULENCE

Persistence restricts the planning model. Elastic persistent and ranged elastic persistent constraints are effective ways to reduce the amount of turbulence between legacy and revised plans, but reducing turbulence can adversely affect the warfighting readiness of a revision.

To assess the effect of persistent restrictions on warfighting readiness, we solve the Rotations model. We then modify the Readiness model to include a constraint that limits the overall turbulence between legacy and revised plans to a fixed number of allowable changes. By incrementally lowering the number of allowable changes and capturing the warfighting effectiveness for each plan, we can see how limiting turbulence affects warfighting readiness. The results are shown in Figure 5.

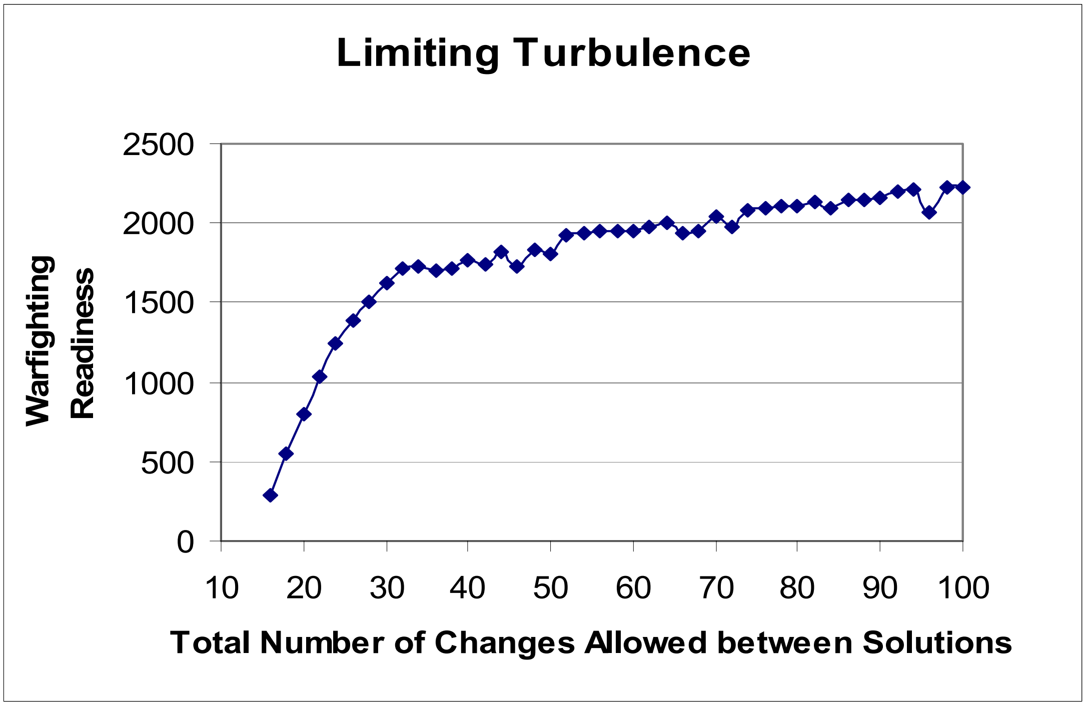

Figure 5. Tradeoff between Warfighting Readiness and Turbulence.
The Readiness model wants to make numerous changes in order to maximize the warfighting readiness of its revision. Restricting the number of changes too much can significantly degrade the overall warfighting readiness of that revision. Each point on this graph represents the objective function value of an integer linear program solved with a relative integrality tolerance of 0.01%: this graph is non-monotonic because each plan has a slight integrality gap.

In terms of the warfighting readiness, DERO wants to suggest a revised plan that differs greatly from the legacy plan. We can limit the turbulence between legacy and revised plans and still maintain a revision with an acceptable level of warfighting readiness. However, once we limit the amount of turbulence to less than 32 changes in this example, the warfighting readiness of our revised plan begins to drop significantly.

Figure 5 shows an important feature of persistence. While limiting turbulence between legacy and revised plans is desired, a persistent revision can exact a price in terms of warfighting readiness. A decision maker must ultimately determine the appropriate balance between the tolerable amount of turbulence between plans and its influence on warfighting readiness. In Figure 5, about 32 changes between legacy and revised plans appear to have a modest impact on warfighting readiness. Fewer than 32 changes will reduce the warfighting readiness of the revised plan too much.

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VI. AUGMENTING OPTIMIZATION WITH A HEURISTIC

A. SENJU AND TOYODA HEURISTIC

Senju and Toyoda [1968] describe a simple method that quickly suggests a near-optimal portfolio of proposals from a large number of possible candidate proposals, where their choices are restricted by consumption of a number of limited resources. Their initial application selects an investment portfolio subject to budget constraints.

Their article describes an efficient way to approximately solve this type of complex problem. Their method solves the following R-Knapsack optimization problem:

Indices:

p	Candidate proposals ($p = 1, 2, ..., P$),
r	Limited resources ($r = 1, 2, ..., R$),

Data:

$benefit_p$	Incremental benefit of proposal *p*,
$available_r$	Limit on availability of resource *r*,
$use_{p,r}$	Proposal *p* would use this amount of resource *r*,

Decision Variables:

$ABLE_p$	Binary decision variable to select proposal *p*,

Formulation:

$$\text{Maximize} \quad \sum_p benefit_p ABLE_p \qquad [1]$$

Subject to

$$\sum_p use_{p,r} ABLE_p \le available_r \qquad \forall r \in R \quad [2]$$

$$ABLE_p \in \{0,1\} \qquad \forall p \in P \quad [3]$$

Verbal Formulation:

The objective function [1] expresses the sum of the benefit of the selected proposals. Constraints [2] ensure that the proposal selections meet the resource constraints. Constraints [3] ensure that each proposal selection is binary.

Senju and Toyoda use a deletion heuristic that begins by adding all of the proposals to the portfolio. If any resource is over-allocated, they describe how to calculate an effective gradient for each proposal in the portfolio. The effective gradient represents the amount of profit lost per resource gained if each proposal is deleted from the portfolio. Proposals are then deleted from the portfolio starting with the proposal with the smallest effective gradient. Senju and Toyoda continue deleting proposals in this order until a feasible portfolio exists.

Pfarrer [2000] uses a Senju-Toyoda heuristic to solve a procurement problem for the United States Special Forces over a ten-year planning horizon. His results show the effectiveness of using this heuristic.

B. USING A FAST SENJU-TOYODA HEURISTIC IN LIEU OF AN INTEGER LINEAR PROGRAM

Following Senju and Toyoda [1968], we develop a heuristic that quickly suggests a near-optimal portfolio of TAMCNs to fund from a large number of possible TAMCNs, where our choices are restricted by their consumption of a limited budget. Unlike the already-discussed optimization techniques, which provide a plan that maximizes readiness across the entire planning horizon, our heuristic is myopic – only maximizing readiness one year at a time.

As described by Senju and Toyoda, we calculate the effective gradient for each TAMCN. But, instead of using a deletion heuristic, we use an addition heuristic that adds TAMCNs to our portfolio in the order of the highest effective gradient. Although DERO is different from the Knapsack model solved by Senju and Toyoda, we are able to generalize their approach to solve the Readiness model.

We begin with the first fiscal year. We first determine the Ready-For-Issue (RFI_t) quantity for each TAMCN t as follows:

$$RFI_t = SRFI_t + ISSUE_t - USR_t + RPR_t$$

As before, the decision variable for our model is RPR_t, which represents the number of TAMCN t to repair. Initially, these variables are all assigned a value of zero (equivalent to not repairing any TAMCNs). We then seek to incrementally add TAMCNs to our portfolio in the order of the highest effective gradient for each TAMCN.

As in DERO, we calculate the effectiveness rating as follows:

$$\text{Effectiveness Rating} = \frac{RFI_t}{WMR_t}.$$

We use this rating to determine the readiness score ($SCORE_t$) of each TAMCN t according to the same piece-wise linear function used in DERO.

We calculate the warfighting readiness ($readiness_t$) gained from incrementally increasing the RPR_t decision variable for each TAMCN t. We then estimate the effective gradient ($benefit_t$) of increasing RPR_t for each TAMCN t. The effective gradient represents the amount of readiness gained per budget lost. We calculate the effective gradient as follows:

$$benefit_t = \frac{readiness_t}{cost_t} = \frac{readiness\ gained}{resource\ lost}.$$

The heuristic incrementally increases the RPR_t decision variable for the TAMCN t with the largest effective gradient. It then re-computes these calculations and repeats additions until a feasible portfolio results within our budget constraints. Once our portfolio has been filled in this manner, it may be possible to add additional TAMCNs with the remaining budget. The pseudocode for the algorithm is as follows:

PSEUDOCODE FOR SENJU-TOYODA HEURISTIC

```
T  – set of TAMCNs t
R_t – number of TAMCN t to repair
G_t – effective gradient
    (readiness gained if R_t -> R_t + 1 per repair cost)
C_t – cost to repair TAMCN t

begin
 B:= available budget
 R_t:= 0 for all t in T
 Calculate G_t for all t in T
 i:= argmax(G_t)
 while B > 0 and C_i < B do
 begin
      R_i: = R_i + 1
      B: = B - C_i
      recalculate G_i
      i: = argmax(G_t)
 end;
 maxbenefit: = 1
 while maxbenefit > 0 do
 begin
      maxbenefit: = 0
      for each i in T do
      begin
            if C_i < B and G_i > maxbenefit then
            begin
                  maxbenefit: = G_i
                  point: = i
            end;
      end;
      if maxbenefit > 0 then
      begin
            R_point: = R_point + 1
            Recalculate G_point
            B: = B - C_point
      end;
 end;
end;
```

Figure 6. Pseudocode for Implementing the Senju-Toyoda Heuristic to Solve DERO.

Each TAMCN is initially assigned zero repairs. We incrementally add TAMCNs to our portfolio in the order of the highest effective gradient until we are unable to afford the next most attractive TAMCN. It may be possible to add additional, less-costly TAMCNs to our portfolio with the remaining resources. Therefore, we spend any additional resources on the TAMCNs with the highest effective gradient that we can afford until our budget is depleted.

The resulting RFI_t for each TAMCN t in the first fiscal year becomes $SRFI_t$ (the starting RFI quantity) for the second fiscal year. We repeat this cycle until our heuristic solves all six fiscal years.

When we compare the overall warfighting readiness produced by this heuristic to DERO's results, we observe the following:

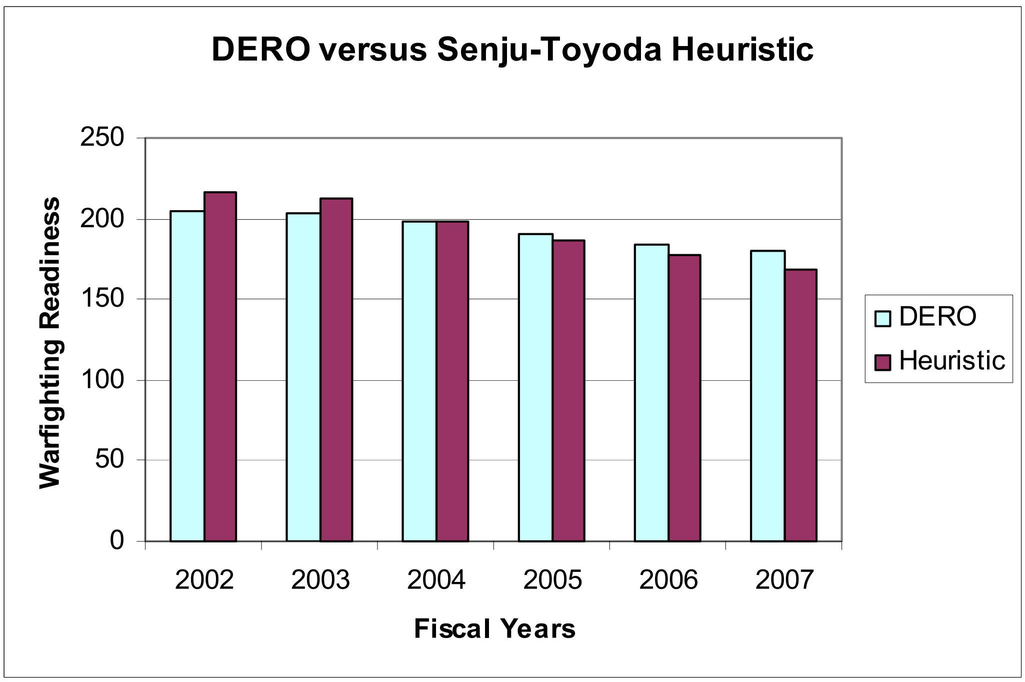

Figure 7. Warfighting Readiness using our Heuristic.
Initially, the heuristic suggests a depot-level maintenance plan with a warfighting readiness that exceeds DERO's plan. By the third fiscal year, the overall warfighting readiness of the two methods is equivalent. The last three years show the myopic nature of our heuristic as DERO produces a plan with a better warfighting effectiveness.

Our myopic heuristic eventually lags behind DERO's omniscient plan because it is unable to look ahead and plan for future requirements in the depot-level maintenance plan. For example, this heuristic will not choose to repair a TAMCN in a current year in order to satisfy a demand in a future year.

Our Senju-Toyoda heuristic is different from DERO. While both models maximize readiness across the planning horizon, DERO provides additional stratification decisions not addressed by the heuristic. Our Senju-Toyoda heuristic does not consider these embellishments.

The primary benefit of our heuristic is its ability to work on readily available software. The entire implementation of DERO, including both the Rotations model and our heuristic, is done with EXCEL™. This is easy to use and quickly provides a depot-level maintenance plan.

Persistence is easy to incorporate in our heuristic. We have described how to implement an addition heuristic based on the highest effective gradient of all TAMCNs. We need only to augment this gradient with persistent terms just like those presented in the persistent integer linear programming. Calculating the effective gradient for a deletion heuristic is also straightforward. Under budget fluctuations, we can easily add or delete TAMCNs from our portfolio based on the appropriately calculated effective gradient.

Although the Senju-Toyoda heuristic performs well, and very quickly, on these test cases, there is no guarantee that it will always work so well. Further, the integer linear program optimization offers a quantitative assessment of solution quality – an absolute upper bound on readiness that might be achieved beyond the current plan suggested – while the heuristic gives no such advice at all. The heuristic, if operated in isolation, offers no clue to the quality of its solutions.

VII. CONCLUSION AND FUTURE AREAS OF STUDY

A. CONCLUSION

Incorporating the persistent constraints suggested in this thesis is an effective way to mitigate the amount of turbulence in DERO when the input parameters are only slightly changed from instance to instance. The added features are shown to be effective when a budget change occurs after a maintenance plan is published. Clearly, these added features provide DERO with greater flexibility and improve the face validity of the model.

While limiting turbulence between a legacy and a revised plan may appeal, we have shown that a persistent restriction can exact a price in terms of warfighting readiness. A decision maker must ultimately determine the appropriate balance between the allowable amount of turbulence between a legacy and a revised plan and that revision’s warfighting readiness. We have described an effective way to develop this decision tool and have shown what it looks like for one data set.

Finally, we introduce a heuristic planning tool to assist in depot-level maintenance planning. Our heuristic is easy to use, quickly produces a depot-level maintenance plan, and works on readily available software. We have greatly reduced the need for expensive licensed software and experienced operators. When used in conjunction with DERO, this tool can provide added insight.

B. FUTURE AREAS OF STUDY

While this thesis demonstrates how to incorporate persistent features into DERO, the same idea can be readily applied to other optimization-based decision support aids used in a manner similar to DERO. When input parameters are only changed slightly between model solutions, the addition of persistent features can provide greater flexibility and improve the face validity of a turbulent model.

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