A Pareto Based Multi-Objective Evolutionary Algorithm Approach to Military Installation Rail Infrastructure Investment

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Abstract: Decision making for military railyard infrastructure is an inherently multi-objective problem, balancing cost versus capability. In this research, a Pareto-based Multi-Objective Evolutionary Algorithm is compared to a military rail inventory and decision support tool (RAILER). The problem is formulated as a multi-objective evolutionary algorithm in which the overall railyard condition is increased while decreasing cost to repair and maintain. A prioritization scheme for track maintenance is introduced that takes into account the volume of materials transported over the track and each rail segment's primary purpose. Available repair options include repairing current 90 gauge rail, upgrade of rail segments to 115 gauge rail, and the swapping of rail removed during the upgrade. The proposed Multi-Objective Evolutionary Algorithm approach provides several advantages to the RAILER approach. The MOEA methodology allows decision makers to incorporate additional repair options beyond the current repair or do nothing options. It was found that many of the solutions identified by the evolutionary algorithm were both lower cost and provide a higher overall condition that those generated by DoD's rail inventory and decision support system, RAILER. Additionally, the MOEA methodology generates lower cost, higher capability solutions when reduced sets of repair options are considered. The collection of non-dominated solutions provided by this technique gives decision makers increased flexibility and the ability to evaluate whether an additional cost repair solution is worth the increase in facility rail condition.

Keywords: Evolutionary Algorithms, Pareto Front, Rail Infrastructure Investment, Rail Repair

1. Introduction

The Department of Defense (DoD) operates and maintains approximately 3000 miles of rail spread across 150 geographically dispersed facilities (Uzarski & Grussing, 2013). This rail infrastructure must compete for funding against other degrading infrastructure to include roads, buildings, and utilities. The current DoD budget environment and the strategic importance of these rail resources necessitate sound analysis of rail infrastructure investments. "The Department of Defense (DOD) manages a global real property portfolio that consists of more than 562,000 facilities—including barracks, commissaries, data centers, office buildings, laboratories, and maintenance depots—located on more than 5,000 sites worldwide and covering more than 28 million acres. With a replacement value of about $850 billion, this infrastructure is critical to maintaining military readiness, and the cost to build and maintain it represents a significant financial commitment." (Office of Secdef) As part of their basic infrastructure, most installations, posts, or garrisons have short haul rail systems used to mobilize and transport supplies and equipment. These rail systems are strategically linked to the national rail network to facilitate transportation of equipment and supplies to key ports and terminals. The current DoD budget environment and the criticality of these rail resources necessitate sound analysis of rail infrastructure investments. The fundamental challenge for leadership is to decide what repairs or replacements to make within the rail infrastructure portfolio to improve the condition of the rail infrastructure, while minimizing repair costs.

The U.S. Army Corps of Engineers Construction Engineer Research Lab (CERL) have developed a decision support tool (RAILER) to inventory, assess condition of, and generate maintenance and repair cost estimates for installation rail infrastructure (Uzarski, et al., 1988). The purpose of this tool is to inform budget decisions related to future repair and maintenance work. Two key modules of RAILER are rail assessment and repair cost estimation. The rail assessment module evaluates and rates the condition of tracks, track segments and overall rail network. Three component groups of each track segment are assessed on a scale of 0 to 100: ballast, subgrade and roadway (BSCI); crossties and switch ties (TCI); and rail, joints, and fastenings (RJCI). These condition indices are based upon the number, type, and severity of defects identified during the inspection process and reflect rail capacity to support typical military installation rail traffic. Lastly, an overall condition index (TSCI) is assigned to each rail segment which is the weighted average of the BSCI, TCI, and RJCI scores. The 0 to 100 scale for each index is subdivided into condition categories with accompanying description of the required repair and maintenance (Uzarski, et al., 1988). Repair costs are itemized by defect (i.e. tie, tie pins, labor, ballast, etc.) and totaled for each track segment. RAILER provides installation managers a valuable decision support tool that inventories DoD rail assets, assesses its current condition, and estimates costs to repair identified defects in order to inform prioritization of rail repair under budget constraints. In this paper we present a Pareto-based alternative to the RAILER repair prioritization approach.

2. Related Research

Liden presents a survey of techniques and analysis applied to rail maintenance planning and scheduling (Liden, 2015). This work highlights application of several mathematical and heuristic techniques, a variety of objectives, and an array of decision variables. The literature reveals numerous potential objective functions with respect to rail maintenance and prioritization to include: life-cycle cost, rail quality improvement, rail quality, weighted rail quality, cost versus rail quality improvement, cost versus rail quality, and down time. Levi utilizes renewal cost as the primary objective to determine rail renewal maintenance scheduling (Levi, 2001). Track quality improvement is used by Oyama & Miwa to evaluate deterioration-based maintenance scheduling (Oyama & Miwa, 2006). A weighted track quality index is used by Murakami & Turnquist as an objective function to analyze critical rail resource scheduling (Murakami & Turnquist, 1985). Miwa employs cost and track quality as a multi-objective approach to machine scheduling in a deterioration-based rail maintenance scheme (Oyama & Miwa, 2006). The fundamental objective utilized in this paper is multi-objective in nature and includes repair cost (minimize) and weighted track quality (maximize).

Researchers have presented several rail maintenance and repair prioritization techniques in the literature. Techniques include expert systems, optimization-based, and computational intelligence approaches. Martland & McNeill present an expert system methodology (REPOMAN) that combines expert opinion of rail condition, rail deterioration models, and economic analysis to recommend scheduling and prioritization of rail repair for Burlington Northern (Martland, et al., 1990). Melching and Liebman develop a heuristic algorithm for solving rail maintenance budget allocation problems via a binary knapsack approach (Melching & Liebman, 1988). Marzouk and Osama create a decision support tool for identifying when to repair groupings of infrastructure (i.e. road and sewage, and electrical) that employs fuzzy logic to model the uncertainty in lifetime of each infrastructure sub-component with the objective of minimizing overall lifecycle repair costs (Marzouk & Osama, 2015). RAILER utilizes a multi-criteria scoring approach which identifies and weights criteria (TSCI, standard condition level, life, etc.) coupled with associated impact factors to generate a priority score for track segments and supporting work items (Uzarski, et al., 1988). Caetano & Teixeira utilize a genetic algorithm approach coupled with Pareto front analysis to recommend scheduling of rail infrastructure sub-components (rail spot repair, ballast tamping, and sleeper spot repair) to minimize both track unavailability and lifecycle cost (Caetano & Teixeira, 2013). While the emphasis of Caetano & Teixeira focus on scheduling of micro level repairs and an offline Pareto analysis, we present a Pareto-based evolutionary algorithm that utilizes the Pareto relationship between solutions as a fitness measure and search mechanism.

Evolutionary algorithms (EA) are a biologically inspired non-gradient optimization technique that allows the rapid and efficient exploration of vast solution space. Evolutionary algorithms have been successfully applied to multiple problem domains including computational fluid dynamics, mobile network design, utility network design, control optimization, mathematical analysis, and production scheduling (McCorkle, et al., 2003; Reina, et al., 2016; Diaz-Dorado, et al., 2002; Zeidler, et al., 2001; Ishibuchi & Murata, 1998; Kirstukas, et al., 2005). Major components of an EA are a population of potential solutions (chromosomes), mechanisms to select, mate, and exchange portions of solutions with each other, and a means to evaluate solution fitness. The advantages of using an EA are that they work well for objective functions that are noisy or not smooth, avoid being trapped in local optimal solutions, can search multiple points in the solution space simultaneously, and can accommodate very large numbers of objective parameters and decision variables. Multi-objective EAs (MOEA) are a special category of EA that consider multiple, often conflicting, objective functions. Approaches to accommodate multiple objectives in EAs can generally be categorized as aggregation-based or Pareto- based. In an aggregation approach objectives are weighted and combined into a scalar value. The objective weights may be fixed or vary as part of the chromosome as in the Hajela's and Lin's genetic algorithm (HLGA) (Hajela & Lin, 1992). Fuzzy inference is a non-linear aggregation approach that has been used in conjunction with EAs (McGill, & Ayyub, 2007; Agarwal, et al., 2015; Pape, et al., 2013; Dojutrek, et al., 2015; Gunduz, et al., 2013). Pareto-based MOEA approaches utilize various dominance measures as a means to evaluate solution fitness and guide exploration of the solution space. Pareto optimality excludes from consideration all alternatives or solutions that provide no additional value over other solutions. A solution to a multi-objective problem is non-inferior if there is no other solution that yields an improvement in one objective without causing degradation in at least one other objective. A primary advantage of the Pareto-based approach is the generation of a collection of near Pareto optimal, non-dominated solutions which allow decision makers to examine and compare the cost vs. benefits of solutions within the non-dominated solution set.

Several literature sources summarize, classify, and critique various MOEA (Coello, 2006; Konak, et al., 2006; Ishibuchi & Murata, 1996). Three current, commonly benchmarked, Pareto-based MOEA are Non-Dominated Sorting Genetic Algorithm (NSGAII), Pareto Envelope based Sorting Algorithm (PESA), and Strength Pareto Evolutionary Algorithm (SPEA2) (Deb, et al., 2000; Corne, et al., 2000; Zitzler, et al., 2001). The primary differences between these Pareto-based approaches are their fitness assignment scheme, diversity mechanism, and use of an external archive. NSGAII clusters solutions into pareto fronts and assigns fitness based upon what front the solution belongs to. Crowding distance is used as a means to maintain solution diversity within the population. NSGAII does not maintain an external archive of solutions (Deb, et al., 2000). PESA utilizes a hyper-grid scheme, evaluating the number of solutions within a particular grid, to control selection and solution diversity. PESA maintains an external archive to preserve non-dominated solutions (Corne, et al., 2000). SPEA2 utilizes count and strength dominance measures to evaluate solution fitness. SPEA2 utilizes a nearest neighbor density estimate to fine tune fitness and truncate excess non-dominated solutions. Laumanns et al. compare the performance of SPEA2 against NSGAII and PESA across a suite of problems with extremely positive results (Zitzler, et al., 2001). In this research, we apply the SPEA2 algorithm to generate a near Pareto optimal rail repair strategy that maximizes rail yard condition while minimizing cost. The SPEA2 algorithm is chosen because of its demonstrated ability to generate solutions that simultaneously converge toward the Pareto front while maximizing diversity of solutions within the approximated front. The remainder of this paper is organized in the following manner. In Section 3, we describe the Fort Smith rail repair problem. In Section 4, we describe our methodology and the SPEA2 algorithm. In Section 5 we present the results of the algorithm performance versus the RAILER solution. Lastly, we present major conclusions and proposed future work.

3. Problem Description

Fort Smith is a typical Army installation which consists of approximately 115 miles of rail. The rail infrastructure is outdated and in poor condition. Recent inspections identified numerous rail condition safety concerns. Of the 104 track segments inspected, one was recommended for restricted operations and 66 were recommended closed to traffic. Additionally, Fort Smith rail is 90 gauge - current industry standard for the type/volume of traffic is 115 gauge rail. The estimated cost of maintenance and repair to render all current track segments defect-free is approximately $13M. The fundamental challenge for Fort Smith leadership is to decide what repairs or replacements to make in what portions of the facility in order to improve the overall condition of the rail infrastructure while minimizing repair costs.

The Fort Smith rail repair and maintenance problem is classified as a multi-objective optimization problem and consists of two competing objectives: minimize cost while maximizing the overall condition of the rail yard, including individual track segment priority. The competing objectives for this problem are highlighted in Equations 1 and 2.

$$\text{Minimize Cost} = \sum_{i=1}^{n} C_{i0}x_{i0} + C_{i1}x_{i1} + C_{i2}x_{i2} + C_{i3}x_{i3} \tag{1}$$

$$\text{Maximize Rail “System” Future Utility} = \sum_{i=1}^{n} p_i fc_i \tag{2}$$

Where: c_{ij} is the cost of repair type j per segment i (i=1,2,3,..104; j=0,1,2,3)
fc_i is the future condition (after repair/upgrade) of rail segment i (Scale of 0-100: Higher better)
x_{ij} is repair type j on rail segment i, and p_i is the priority of rail segment i (Scale of 0 to 1)

Available repair options include: do nothing, repair the rail segment as recommended by RAILER to improve the condition index to 100, completely refurbish the rail segment and upgrade to 115 gauge, or swap good condition rail from low traffic/low priority segments to high priority, poor condition segments. The repair options can be represented by the decision variables.

There are several considerations that influence rail repair investment decisions. First, track segments within the Fort Smith rail complex have differing purposes. The primary purpose of track segments at Fort Smith can be categorized as storage, production, access, or transit. Track segments that provide access to and from the external rail infrastructure and production lines are considered more important than those primarily utilized for intra-yard transit or storage.

Table 1. Decision Variables

Variable	Definition
x_{i0}	Do nothing to segment i
x_{i1}	Repair rail segment i with 90 gauge rail
$\boldsymbol{x_{i2}}$	Upgrade rail segment i with 115 gauge rail
$\boldsymbol{x_{i3}}$	Swap rail segment i

Second, given the nature of typical operations at Fort Smith, rail segments within the complex have varied traffic volumes. For example, rail associated with access and production has a much higher traffic volume than segments associated with storage. Lastly, the condition and associated repair costs for each rail segment vary greatly. Each of these factors both inform and increase the complexity of repair and maintenance investment decisions at Fort Smith.

4. Methodology

This research applies a frequently cited, commonly benchmarked, multi-objective evolutionary algorithm; the Strength Pareto Evolutionary Algorithm (SPEA2) (Zitzler, et al., 2001). SPEA2 was selected because of its common use as a benchmark for multi-objective EAs. The technique produces a near Pareto optimal front, vice a single solution, which provides the decision maker the opportunity to consider trade space analysis. SPEA2 also works to eliminate solutions that are “similar” by using a unique density calculation to maintain diversity or spread along the Pareto front. Prior to employing the SPEA2 algorithm, it is necessary to collect important rail segment data, pre-process the data to account for rail segment transit volume and segment purpose, and transform the problem into a form compatible with an EA construct.

4.1 Data Requirements and Pre-processing

The major data elements utilized to formulate and solve the Fort Smith rail repair problem include: rail segment length, rail segment cost for each type of repair, primary rail segment purpose, annual segment traffic volume, and rail segment post repair condition score for each repair option (Table 2). Data pre-processing for this problem requires transformation of rail segment volume and purpose into a normalized track segment priority score to account for difference in traffic volume and segment functionality.

Table 2. Sample of Fort Smith RAILER Condition and Repair Cost Data

Segment	Distance (Ft)	Cost_0 Do Nothing	Cost_1 Repair	Cost_2 Upgrade	Cost_3 Swap	Purpose	Yr Volume	TSCI_0 Do Nothing	TSCI_1 Repair	TSCI_2 Upgrade	TSCI_3 Swap
1	1193	2.0578	20.578	225.947	5.1445	Transit	120	89	100	115	95.6
2	7920	9.3821	93.821	1500	23.45525	Transit	120	85	100	115	94
3	7081	22.5316	225.316	1341.099	56.329	Access	240	69	100	115	87.6
4	2360	3.3103	33.103	446.9698	8.27575	Access	240	75	100	115	90
5	2328	4.3968	43.968	440.9092	10.992	Access	240	74	100	115	89.6
6	2334	4.8004	48.004	442.0456	12.001	Access	240	72	100	115	88.8
7	2317	4.751	47.51	438.8259	11.8775	Access	240	72	100	115	88.8
8	2821	1.2197	12.197	534.2805	3.04925	Access	240	63	100	115	85.2
9	5350	21.3995	213.995	1013.258	53.49875	Access	240	64	100	115	85.6
10	1122	3.2142	32.142	212.5001	8.0355	Access	240	66	100	115	86.4

Typical maintenance decisions include consideration of some aspect of criticality whether it is traffic volume, mission, purpose, or degree of redundancy. Usarski & Grussing introduce a knowledge–based rail inspection prioritization methodology (Uzarski & Grussing, 2013). They develop a mission-based scoring index that is a function of track segment priority, track

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segment condition, track segment condition degradation rate, and serious defect rate. The track segment priority is a weighted combination of segment transit volume (with consideration of HAZMAT movements), and track segment mission or purpose. In this paper, we utilize a variant of the Usarski & Grussing track prioritization scheme (Uzarski & Grussing, 2013). First, monthly dispatch reports that detail Fort Smith rail movements within the complex were compiled and analyzed. This data allowed us to determine annual rail segment traffic volume for each rail segment within Fort Smith. The annual rail segment traffic volume is converted to a normalized traffic score (NTS) by dividing the track segment volume by the maximum annual volume for a segment within the complex. Next, we categorize each rail segment into one of four categories: access, production, transit, and storage. Fort Smith rail managers prioritized and provided a weighting factor for each track segment category (Table 3). Note that rail segments that primarily provide access in and out of Fort Smith are assigned the highest priority and those primarily associated with storage received the lowest priority and weighting.

Table 3. Rail Segment Purpose/Priority

Primary Role	**Priority**	**Weight**
Access	1	0.50
Production	2	0.30
Transit	**3**	**0.15**
Storage	**4**	**0.05**

A rail segment priority score is formed as the product of the normalized traffic score and the rail categorization weighting (Equation 3). Finally, Rail segment priority scores are then normalized resulting in a rail segment priority score ranging from zero (0) to one (1).

$$\text{Rail Segment Priority Score} = NTS * \text{Rail Purpose Weight} \tag{3}$$

4.2 Transform Problem into MOEA Construct

Identify solution representation scheme. An evolutionary algorithm requires that the solution alternatives be encoded as a string (chromosome). Solution alternatives can be encoded according to several formats including: binary, integer, or numerous other combinations. We encode Fort Smith rail segment repair solution alternatives as a length 208 binary strings. Each string is composed of 104 repeated two bit sub-sequence. Each sub-sequence translates to 0, 1, 2, or 3 which correlates to: do nothing, repair, upgrade, or relay that particular rail segment.

Identify Fitness function. SPEA2 employs a count and rank-based dominance fitness measure to quantify the quality of candidate solutions. As such, a strength (S) and raw fitness (R) score are calculated for each solution. P_t is the population at generation t and $\overline{P_t}$ is the archive at generation t.

$$S(i) = |\{j \mid j \in P_t + \bar{P}_t \wedge i \succ j\}| \tag{4}$$

The strength score, highlighted in Equation 4 above, indicates the number of other solutions a particular solution dominates. The objectives in this paper are cost and overall rail condition of the complex and we seek to maximize condition while minimizing cost. One solution dominates another if a better condition is generated at a lower or equal cost compared to the competing solution.

$$R(i) = \sum_{\boldsymbol{j} \in \boldsymbol{P_t}+\bar{\boldsymbol{P}}_t,\ \boldsymbol{j} \succ \boldsymbol{i}} \boldsymbol{S(j)} \tag{5}$$

The raw fitness (R) score, highlighted in Equation 5 above, indicates the total number of other solutions that dominate a particular solution. Note that solutions with an R score of zero are non-dominated solutions. Solutions are further differentiated by adding a nearest neighbor density factor to the raw fitness score. SPEA2 utilizes a nearest neighbor density estimate to both fine tune fitness and delete excess non-dominated solutions from the archive. The calculation of the density estimate (D) is shown in Equation 6 below. K is the square root of the sum of the population size (N) and the archive size (ÑN̅N̅). Note that solutions with a larger kth nearest neighbor (farther away from neighbor solutions) will have a smaller density score.

$$D(i) = \frac{1}{\sigma_i^k + 2} \qquad \text{where} \qquad k = \sqrt{N + \bar{N}} \tag{6}$$

The final fitness (F) of each solution or chromosome is the sum of the density estimate and the raw fitness (Equation 7).

$$F(i) = R(i) + D(i) \tag{7}$$

MOEA Operational Parameters. Evolutionary algorithms employ several operational parameters that control the evolution of solutions as subsequent generations are produced. These parameters include population size, archive size, selection technique, crossover rate, mutation rate, and termination criteria. Population size represents how many solution alternatives will be generated, evaluated, and carried forward from generation to generation. The selection function determines which solution alternatives will "survive" to the next generation. Selection techniques include: proportionate, roulette wheel, and tournament schemes. Crossover entails the exchange of solution segments between paired or mated chromosomes and mutation is the random variation of a gene within a chromosome. An EA can typically be terminated via several criteria to include: number of generations or solution improvement. Under the number of generation termination criteria, the EA is stopped once the max generations are reached. A solution improvement-focused termination criteria identifies a solution improvement threshold. If solution improvement "stalls" or does not exceed the solution improvement threshold, the EA run is terminated. Note that extensive research has been conducted regarding the appropriate settings for these key operational parameters and is outside the scope of this paper [Uzarski & Grussing, 2013; Uzarski, et al., 1988; Liden, 2015; Sangkawelert & Chaiyaratana, 2003; Shukla, et al., 2015; Wang, et al., 2066; Eiben, et al. 1999). Table 4 highlights the major operational parameters for our multi-objective EA approach.

Table 4. MOEA Operational Parameters

Parameter	Value
Population Size	50
Archive Size	20
Selection Technique	Binary Tournament
Crossover Rate	0.90
Mutation Rate	0.10
Termination Criteria	1000 Generations

4.3 SPEA2 Algorithm

SPEA2 is a multi-objective, Pareto-based EA approach that employs a count and rank-based dominance fitness measure to drive solutions toward the Pareto optimal front. SPEA2 employs an elitist strategy in that it maintains an external archive of solutions and exclusively produces new solutions from the archive members. SPEA2 also utilizes a nearest neighbor density estimation technique which is used to differentiate solutions and maintain solution spread (diversity) within the archive. The pseudo code for the SPEA2 algorithm is highlighted in Figure 2 below (Zitzler, et al., 2001).

The SPEA2 algorithm begins with a population and an empty external archive. The external archive is an application of EA elitist strategy in which a collection of high quality solutions are maintained and used exclusively for mating of future generations. Typically, the archive size is equal to the population size. However, that is not necessary and in this research we utilize an archive size less than the population size (i.e. 20). Next, the fitness values, which are Pareto dominance based measures, are calculated for both the population and archive. The specifics of the fitness measure are detailed in the following section. All non-dominated solutions from the population and archive are copied to the subsequent archive. If the number of non-dominated solutions exceeds the archive size, excess non-dominated solutions are deleted from the archive based upon on a nearest neighbor density measure, D (Equation 6).

A mating pool is formed using binary tournament selection. Members of the mating pool are randomly paired for recombination of genetic material to form new offspring or solutions. We utilize single point crossover and bit flip mutation as the primary recombination operators. The above process is repeated until termination criteria, in this case number of generations, are met. At termination, the output of the algorithm is the approximated Pareto front represented by the final archive.

SPEA2 Algorithm	
Step 1:	Generate initial population P_0 and empty archive A_0. Set t = 0.
Step 2:	Calculate fitness values of individuals in P_t and A_t
Step 3:	A_{t+1}= non-dominated individuals in P_t and A_t. If size of A_{t+1}> N then reduce A_{t+1}, else if size of A_{t+1}< N then fill A_{t+1} with dominated individuals in P_t and A_t
Step 4:	If t > T then output the non-dominated set . Stop.
Step 5:	Fill mating pool by binary tournament selection with replacement on A_{t+1}.
Step 6:	Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. Set t = t+1 and go to Step 2.

Figure 2. SPEA 2 Pseudo Code

5. Results

The Fort Smith rail repair problem was formulated and solved utilizing the SPEA2 algorithm with an archive size of twenty and several different random number seeds. Multiple random number seeds (30) were used to ensure the solutions obtained were not merely a result of the randomly generated initial population. It is recognized in the literature that the SPEA2 algorithm has above average computation burden with the inherent requirement to conduct pairwise comparison calculations of the population and archive strength (S) scores, the raw fitness scores (R), and the nearest neighbor density estimates (D). The average algorithm run time for an archive size of 20, population size of 50, and 1000 generations was 354 seconds. In this section, model output is examined, in general, as well as in comparison to the RAILER generated prioritized, worst first solution.

5.1 Examining all possible repair options

Table 6 highlights the generalized model output for 30 random number seeds with 1000 generations per run, an archive size of 20 and a population size of 50. While generating this output, the MOEA considers all possible repair options (i.e. Do nothing, repair, swap, or upgrade to 115 lb). Table 5 highlights the maximum possible condition and minimum cost. The Fort Smith as is condition score is 560.38. The maximum possible condition score is 884.19 which occurs if all rail segments are upgraded to 115 lb. rail with a cost of $84.345M. The minimum possible cost is $1.291M and occurs if zero repairs are made and results in no change to the current condition score (560.38). This is the case because even if repairs are not made, a maintenance cost is incurred. Across all 30 random number seeds, 561 non-dominated solutions were generated. The best condition score, across all random number seeds, was 841.96 at a cost of $27.46M. The minimum cost, across all random number seeds, was $5.65M with a resulting condition score of 693.97.

Table 5. General Output Results all Seeds

MOEA Cost and Condition Results	
Max. Possible Condition (Cost)	884.19 ($84.245M)
Min. Possible Cost (Condition)	$1.291M (560.38)

Table 6 summarizes the general pattern across all 561 non-dominated solutions generated for all random number seeds. In general, non-dominated solutions highlight a preference for repair or swap of rail segments. The least recommended repair options across non-dominated solutions are do nothing and upgrade rail segment from 90 gauge to 115 gauge likely due to the $1M per mile cost for this upgrade.

Table 6. Repair Recommendations across all Non- Dominated Solutions

Do Nothing	Repair	Upgrade	Swap
19.04%	32.10%	22.01%	26.85%

As noted earlier, RAILER recommends repairs based upon a prioritized, worst-first strategy. Table 7 highlights the top ten recommended repairs for this repair strategy. Since RAILER only considers repair or do nothing as options, the best possible condition attainable is 768.8 at a cost of $12.9M.

Figure 3 highlights the MOEA results for a single seed with all repair options considered. All repair options included in the "all options" MOEA are not considered by RAILER, (swapping of rail segments and upgrade segments to 115 gauge). Upgrade of rail segments provides a substantial improvement in rail condition at a correspondingly large cost which explains the large shift in the cost versus condition plot and the fact that all MOEA solutions achieve a higher condition.

Table 7. RAILER Top 10 Recommended Repairs

	Segment	**Priority**	**Condition**	**Repair Cost**
1	52	1.0	73	$19.175K
2	47	.48	73	$221.916K
3	45	.48	74	$14.928K
4	46	.48	74	$23.534K
5	95	.28	71	$303.219K
6	84	.17	74	$132.53K
7	85	.16	71	$21.222K
8	96	.14	68	$200.571K
9	83	.14	70	$111.003K
10	8	.13	63	$12.197K

However, RAILER solutions in the $10M to $13M range are dominated by the MOEA generated solutions-the MOEA solutions in this range provide higher condition for equivalent cost. Given the inconsistency in repair options considered, to make an objective comparison to RAILER, the results from the MOEA with a repair only option are compared to RAILER.

5.2 Examining reduced repair options

The previous section highlighted MOEA results when all repair options are considered. In this section, the MOEA results are examined while considering a reduced set of repair options to highlight the benefit of the MOEA approach over RAILER. Figure 4 shows MOEA versus RAILER performance when considering a repair only option. RAILER applies a greedy heuristic to identify potential installation rail repair alternatives.

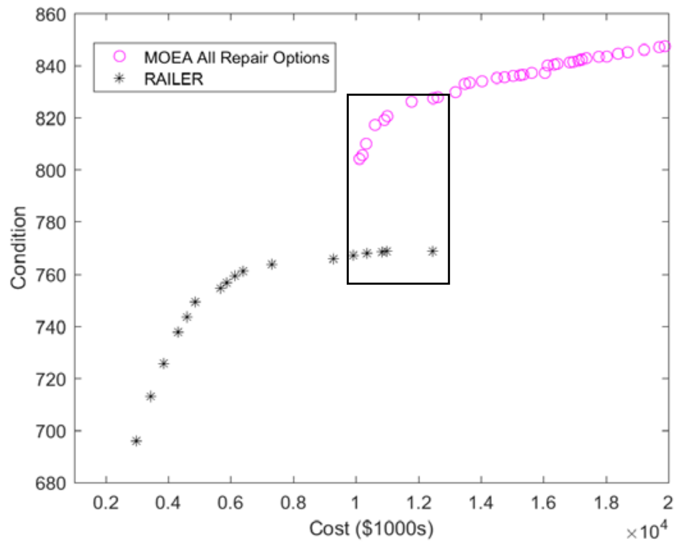

Figure 3. Multi-Objective EA and RAILER Comparison (All Options)

The methodology employs a prioritized, worst-first technique that generates a list of repair options without consideration of overall cost – repairs are executed in accordance with the prioritized list until funding is depleted. The MOEA, however, considers both condition and cost as it explores alternatives in the solution space. In general, the MOEA identifies solutions near the knee in the condition- cost curve and then begins to identify solutions spread about the knee in the curve. When only the repair option is considered, the MOEA approach identifies solutions that provide higher condition scores at a lower cost in the $2M to $7M cost range. Additionally, none of the MOEA solutions are dominated by RAILER solutions.

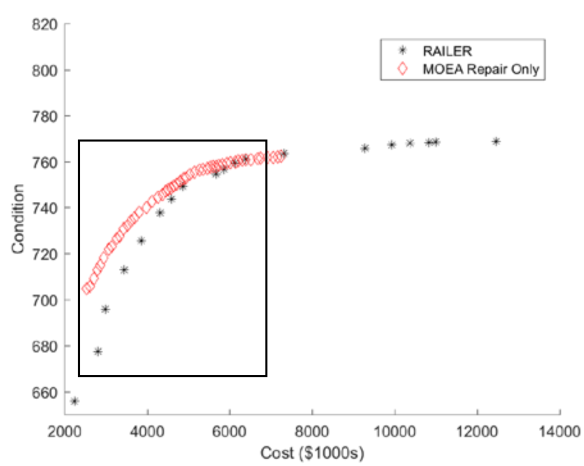

Figure 4. Multi-Objective EA and RAILER Comparison (Repair Only)

Swap of rail segments is an alternative often considered when high priority, high volume segments are degraded to the level that requires implementation of safety restrictions that have an adverse impact on rail operations. Therefore, inclusion of a swap repair option is included in this research. When repair or swap options are considered, the MOEA approach identifies solutions that provide higher condition scores at a lower cost in the $2M to $5M cost range (Figure 6). Additionally, none of the MOEA solutions are dominated by RAILER solutions. Although cost and condition are weighted equally, the MOEA results tend to favor condition which is likely due to the mix of high and medium priority rail segments (80%) versus low priority rail segments (20%). Because the MOEA simultaneously considers cost and condition, while RAILER only considers condition without a cost constraint, rail segments with extremely large cost-condition ratios are excluded from the MOEA solutions which explains the limited cost growth depicted in Figures 5 and 6.

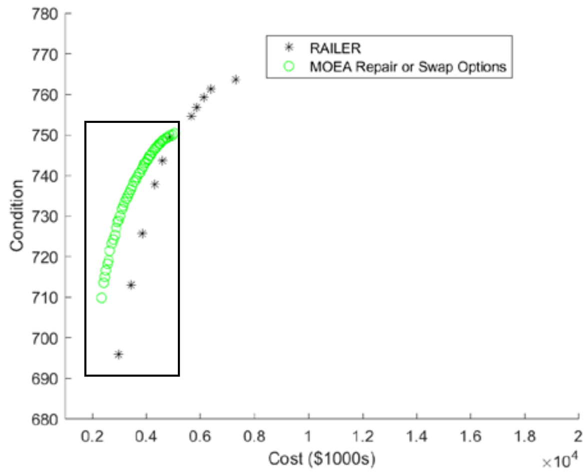

Figure 5. Multi-Objective EA and RAILER Comparison (Repair or Swap)

6. Conclusion

In this research, we employ a Pareto-based MOEA (SPEA2) to the Fort Smith rail repair problem. The problem is formulated as a multi-objective EA in which we attempt to increase the overall railyard condition while decreasing cost. A track segment prioritization scheme is introduced that incorporates transit volume and rail segment primary purpose. Additional repair options including upgrade of rail segments to 115 gauge rail and swapping of rail are included for consideration which give decision makers additional options beyond those currently considered in RAILER (i.e. do nothing or repair).

The proposed MOEA approach provides several advantages to the RAILER approach. The MOEA methodology allows decision makers to incorporate additional repair options beyond the current repair or do nothing options. It was found that many of the solutions identified by the evolutionary algorithm were both lower cost and provide a higher overall condition that those generated by DoD's rail inventory and decision support system, RAILER. Additionally, the MOEA methodology generates lower cost, higher capability solutions when reduced sets of repair options are considered. When restricting repair options to repair only, the MOEA selects rail segments with low condition and low cost to repair because it considers multiple objectives whereas RAILER only considers the lowers condition rail segment. This phenomenon was also observed when examining repair options that included repair or swap only. The presented MOEA approach generates a collection of Pareto optimal solutions based upon these two objectives and therefore is able to create compromise solutions that RAILER is not capable of providing. From a DoD perspective, the MOEA approach allows increase of rail infrastructure condition under financial constraints and budget cuts. Under conditions of uncertainty, this collection of non-dominated solutions give decision makers both flexibility and the ability to evaluate whether an additional cost solution is worth the increase rail condition. There are several areas for additional research related to the Fort Smith rail repair investment problem as well as the algorithms employed to solve it. An experimental design examining the key EA parameters (archive size, population size) effect on generated solutions and their diversity provide a valuable research opportunity.

7. References

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