



# *Wind Turbine Blade Maintenance Strategy Analysis Using Integer Programming Techniques*

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## Abstract

The study provides a data-based model to evaluate the organizational risk associated with service and maintenance of a fleet of 4500+ wind turbines with 13,500+ wind turbine blades across the North American operations of a global wind turbine designer, manufacturer, installer and servicer. This study provides a basic model that can be used to assess the cost trade-offs between growing a blade service organization to more effectively repair damages blades and operating wind turbines with damage with the risk of possible failure.

## Background

Wind turbine blades experience damage as a result of exposure to the environment, product degradation and product defects. Blade damage can occur due to ice damage, bird strikes, lightning damage, manufacturing defects, improper repair procedures and operation in extreme conditions. This analysis is to be performed from the perspective of a North American wind turbine service organization; in many cases, this organization has long-term service agreements negotiated for a fixed price to maintain wind turbine components when subjected to damage. Under the typical terms of a service agreement, all damage to blades that can eventually affect the performance of the turbine must be repaired by the servicing organization. Under this contractual structure, when damage to a blade occurs, the service organization is obliged to repair the blade. If further damage or catastrophic damage occurs to the blade after any pre-existing damage has been identified, the blade service organization is financially responsible for the further damage, potential catastrophic damage requiring costly blade replacement, as well as any resulting harm to the environment or personnel surrounding the turbine.

The costs associated with blade repair or replacement can be substantial; specifically, crane costs associated with blade repair or replacement can be significant. Blade repairs can be completed “uptower”, or in the air using crane access, or “downtower”, which required the blade to be lowered to the ground for service. Crane costs to access a blade uptower to execute minor repairs before damage propagates to significant level is on the order of \$10,000-\$20,000 per repair, while crane costs to mobilize and construct a large crane capable of lowering a blade to the ground is on the order of \$75,000-\$125,000. Clearly large financial

gains can be made by repairing blades before damage propagates to severe levels; similar financial gains may be possible by minimizing risk associated with continued operation of turbines with unrepaired blades.

The specialized know-how required to repair composite material blade constructions limits the number of qualified personnel capable of performing repairs; organizations must spend significant amounts of time and money to train and support these specialized resources. Just as blade repair and replacement requires a significant investment, training a blade repair technicians may require \$35,000-\$50,000 per technician.

Other key considerations that must be factored into a strategic approach for blade repair is the environmental conditions that may affect blade repair operations. Restrictions include allowable windspeeds when uptower repair work can be performed, allowable temperatures and relative humidity ranges that are compatible with composite materials required to perform repairs. In many regions of North America, only small windows of time that have favorable weather conditions exist to complicate the management and planning for blade repairs.

## Literature Review

The need to service and maintain distributed equipment is not unique to the wind turbine industry. In fact, it is a problem that many industries and companies have tackled in the past and will face in the future. In any problem of this nature, it is most important to recognize the cause of failure and understand what the distribution of time to failure may look like. Bluntly, the company that we are working with is just starting to look at data in this manner. However, it appears that the failures are occurring based on outside influences on the system. If the failure rate could be predicted by fitting the proper failure data to a distribution, such as log-normal or a Weibull with some shape parameters, it would be possible to develop a holistic maintenance program that would incorporate preventative repairs. If the failure rates do follow some distribution, then the physics of failure would dictate that the problem is a type of constant failure rate or perhaps a wear-out mode that would increase in frequency as a function of some independent variable.

At the current stage of maturity, both our project team and the company that has provided the service data will investigate the total reduction of needed repairs in the field, given the constraints that have already been discussed. The basic framework for the objective function is found and slightly modified from literature that has explored the scheduling of maintenance technicians for equipment that is installed over a large geographic region. [1] If the

failure rate is random or stochastic in nature, a preventative maintenance scheme would be very difficult or perhaps even impossible to optimize. However, many companies and academics have taken this approach, as the benefits from a strategic service plan are substantial. A failure rate that could be random in occurrence could be driven by factors that cannot be reasonably predicted or forecasted, such as weather or other acts of God such as earthquakes or tornados. Modeling and optimization of stochastically driven systems is inherently more difficult and frankly not within the scope of the toolset that we have been exposed to. For the purposes of this project, the anticipated scope of work has been estimated based on known damages observed through inspections, a heuristic evaluation of damage degradation over time, and an estimated number of additional damages that occur over time based on historical experience.

### **Cause and effect:**

The problem becomes more interesting when the equipment to be serviced is distributed geographically making the service costs higher and logistics more difficult to plan. The problem that we set out to investigate has failures that seem to be caused at random, or be largely random in nature. The majority of failures are not simply wear out failures that can be easily predicted. The onset of the failures is highly dependent on weather patterns and isolated events such as storms, lightning, ice damage and exceedingly high winds. Given that there are many installation sites within North America and each site has its own weather patterns which are highly variable from year to year, the manufacturer of the wind turbines that we have been studying has not been able to identify a recognizable pattern on a time scale that can be analyzed by an optimal model.

There are examples in literature where companies have been able to determine a pattern and then define a maintenance plan. In these instances, Operation Research tools are often employed. For instance, Operation Research tools have been used to define a strategic plan to maintain and replace bridges. This optimization model was largely based on the probability of failures and it is recommended that the wind turbine manufacturer track data so that these probabilities are better understood on per installation and per turbine model basis. It is quite possible that advance data mining techniques will need to be employed to gain meaningful insight to this activity. In the bridge example, the physics of failure, such as corrosion also was a significant part of developing the constraints and assumptions of the model.[2]

**Methods used to optimize operations:**

When the failures are stochastic, additional methods and numerical analysis are utilized to determine an optimal or nearly optimal solution. Other work has investigated manufacturing machinery repair related to downtime of a manufacturing line. The financial repercussions of this situation are far reaching from the product manufacturer's point of view. Not only does the manufacturer have to pay for the cost of repair, but they also aren't able to produce power during periods of down time, which costs the company even more money and a potential loss of customers. All of these implications help to illustrate how this potential issue has a ripple effect on a manufacturing company, and reiterates the importance of having a model in place that can effectively address such operational challenges.

Linear Programming is an appropriate toolset that has been used to analyze these issues since the constraints are fairly easy to identify. Data required to define the problem formulation is relatively convenient to collect and understand, some of which are common metrics and descriptors used in reliability engineering. Specific examples of these metrics are Mean Time to Failure, Mean Time to Repair, and decreasing failure rates as judged by one of the shape parameters of a Weibull Distribution. Mean Time to Failure and Mean Time to Repair are very analogous to Interval Time and Average Service Time from Queuing Theory methods and approaches. An article presenting this problem also reveals that the researchers have employed aspects of goal programming into their model as well. [3] The methodology described in the above reference is quite holistic in its approach and has the appearance of being quite comprehensive in the inclusion of nearly all impacted metrics. It is important to note that this work is based on age-dependent failures; which imply that the dependence of failure rate with time in the field is understood and predictable, unfortunately this analysis does not have that luxury due to limitations in available data. Given all of these facets, the problem is a very interesting one that can utilize many methodologies from Operations Research.

In a similar vein as the above work, other academics have considered the serviceability intervals of paper making equipment and have incorporated the use of an Analytical Hierarchy Decision Making process, along with Operations Research approaches, to help balance the multiple competing objectives that may fall out of a preventative maintenance scheduling problem. [4] The roots of this "conflict" are production needs and maintenance needs. Chareonsuk, et al. highlights that solving this problem looking only at one of these two points of

view at a time does not truly result in an optimized system. To perform this task, a good understanding of the underlying failure distributions is required. With an understanding of the physics of failure, the authors are able to estimate the three shape parameters for the Weibull that accurately describe the failure rates and their onset.

Such advanced analysis techniques have far reaching value for the application of this model; utilization of the prior art on the subject is recommended as a carryon step to this fundamental optimization analysis.

### Methodology & Model Development

Following a literature review to understand prior research and possible approaches to analyze the wind turbine service issues, an algebraic model was developed to model the key considerations and constraints of the blade repair operation issues. Next, data was compiled for the purpose of this analysis using Excel to compile and calculate the risk on a site by site basis for the calendar year 2012 by considering the known scope of damage, estimated degradation of damages through the year, estimate new damages to occur in 2012 and customer priority. The scope of work for calendar 2012 was determined by categorizing known and anticipated damage levels, and associated a typical estimated repair time for each category of damage. The calculations for total days of work and total risk coefficient for each site is shown below in equations [1] and [2]:

[1]

$$\begin{aligned} \text{Total Days of Work For Each Site} \\ = \text{total number of repairs each damage category} \\ \times \text{days required to repair each damage category} \end{aligned}$$

[2]

$$\begin{aligned} \text{Total Risk Coefficient For Each Site} \\ = \text{Damage severity for each repair} \\ \times \text{number of damages} \\ \times \text{risk of damage damage leading to blade failure in next 6 months} \\ \times \text{customer priority} \end{aligned}$$

The risk of damage leading to blade failure in the next 6 months was assigned a value ranging between zero and one based on estimated damage propagation rate with one indicating certain blade failure. Customer priority, an indicator of the turbine seller to sell additional turbines to in the future, was also assigned a value ranging between zero and one, with zero indicating no possibility for future sales. The total risk coefficient for each site is a general indicator of organizational risk specific to each site. Each site risk must be calculated separately due to the potential for each site to be owned by separate energy producers. The tabulated results for the risk and work scope are provided in Appendix I.

Next, the optimal weather repair window for each site was defined based on meteorological conditions observed through historical data for each site, including temperature, windspeed and relative humidity. This information was collected based on the requirements to complete composite blade repair and historical site specific meteorological data such as windspeed, ambient temperature and relative humidity.

After calculating and tabulating site specific risk coefficient, scope of work, and days of the year when conditions were feasible for repair, GLPK was identified as the best software package to process the large amount of data and complex data structures posed by this problem. Using GLPK to evaluate the optimal manpower allocation strategy to reduce risk within weather constraints, with varying the available technician manpower, the overall organizational risk can be calculated based on the assumptions and constraints discussed in this analysis. .

The desired output of the GLPK software is a “days of work” value for each site based on an optimal strategy to minimize risk. This work schedule can then be incorporated into the tabulated Excel data for initial risk at each site to finally tabulate the remaining organizational risk based on the number of technicians assigned to execute work.

To validate the model results, the above model was implemented on a single region within the blade service organization of five wind sites, with possible work days in the year consisting of 365 days starting January 1, 2012. The total number of blade repair technicians were varied from zero to a sufficiently large number such that all required work could be completed to eliminate all risk. Limiting the analysis to one service region allows for close inspection of the analysis results to confirm the model is valid for the remaining North American service regions.



## Model Assumptions

The algebraic model developed includes the following assumptions and constraints:

### **Number of damaged blades (planned on annual basis):**

A large backlog of blade damages (identified but unrepaired blade damage) exists; new damages occur based on seasonal trends associated with weather conditions. The scope of work considered in this analysis considers known blade damages and estimated additional blade damages expected for 2012. It is assumed that each known damage will degrade one category level in severity over a 6 month period of continued operation.

### **Repair Time (varies depending on damage severity):**

Identified damages are categorized by damage severity so repairs that estimated time to repair each category of damage can be easily calculated along with the risk of each damage. Similarly, the time required to repair each damage is based on severity of damage. For the purposes of this analysis, it is assumed that a repair requiring one day of work will be completed in one day. No efficiency considerations are included, for example, a repair requiring eight man-hours may require significantly more actual hours to complete due to weather variations or other operational challenges.

### **Damage Severity - Risk (varies as a function of time):**

Identified damages are categorized by damage severity so repairs that estimated time to repair each category of damage can be easily calculated along with the risk of each damage.

### **Weather Conditions (known based on historical data):**

Blade repairs can only be performed in temperatures above 15 degrees Celsius and relative humidity below 70%. Uptower blade repairs cannot be performed in wind speeds above 15 m/s for safety reasons. Weather cannot be precisely forecasted, but general regional and seasonal weather trends will be used to assess the suitability of weather conditions necessary to perform repairs at each site. Execution of work when weather

conditions are most optimal for repair should be maximized. For the purposes of this analysis, no limitations on the potential days of work (such as technician vacation days, holidays, etc) were considered.

### Customer priority (known value):

Key customers are a focus of blade service as they represent the highest revenue stream for future repair service contracts; customer priority will be classified into high, medium, low and very low based on the importance of key accounts to future service agreements. Attention to high priority customers should be maximized.

### Number of technicians:

The number of technicians can be varied through user defined input in GLPK code; the number of technicians is to be varied from 0 to a sufficiently large number that will eliminate all risk so a full understanding of risk and technician headcount can be modeled.

## Algebraic Model

$$\max : \sum_j R_j - \sum_i \sum_j \sum_k W_{i,j,k}$$

s. t.

$$\sum_i \sum_j \sum_k W_{i,j,k} = \frac{R_j}{D_j} \sum_{i=0}^n \sum_{k=0}^n Y_{i,k} \quad \forall j$$

[Converts days of work completed to a risk value]

$$\sum_k Y_{i,j,k} \quad \forall i \quad \forall k \leq 1$$

[A technician can only work at one site for each day of good weather]

$$\sum_i \sum_k (Y_{i,j,k}) \leq D_j \quad \forall j$$

[Work days completed at site j ≤ work required at each site j]

$$W_{i,j,k} \geq 0 \text{ [Non - negativity]}$$

Where:

$$\begin{aligned} R_j &= \text{Risk at site } j \text{ estimated for 2012} \\ W_{i,j,k} &= \text{Risk estimated by technician } i \text{ at site } j \text{ on day } k \\ i &= \{1, 2, 3, \dots, N\} \text{ [N technicians]} \\ j &= \{1, 2, 3, \dots, S\} \text{ [S sites]} \\ k &= \{1, 2, 3, \dots, 365\} \text{ [365 days in 2012]} \\ Y_{i,j,k} &= \begin{cases} 1, & \text{if work is feasible on site } j \text{ on day } k \\ 0, & \text{otherwise} \end{cases} \\ D_j &= \text{Total days of work planned for site } j \end{aligned}$$

## Parameters and Variables

**Defined Parameters:**  $R_j, i, j, k, D_j$  are all known parameters; While  $i$  varies to generate a final risk number, it is a user defined variable that is input into the integer program.

**Variables:**  $Y_{i,j,k}$  is the only variable in the equation, which represents the placement of technicians at each site on each day of the year.

### Constraint Formulas:

[3]

$$\sum_i \sum_k (Y_{i,j,k}) \leq D_j \quad \forall j$$

Constraint equation [3] limits the total days of work from exceeding the required days of work anticipated for the fleet at all sites.

[4]

$$\sum_k Y_{i,j,k} \forall i \forall k \leq 1$$

Constraint equation [4] limits each site to one technician for each day

### Model Validation and Implementation

The above algebraic model was translated into GLPK code with additional modifications to the model strategy required to implement the above algebraic constraints. A notated copy of the GLPK code is provided in Appendix II. Due to challenges and limitations when implementing the above algebraic model in GLPK, an additional constraint must be defined in order to ensure that the GLPK model is utilized properly--the model presented here is valid when the total days of work required to be completed at each site is less than the total number of potential good weather days at the site in on year. If this condition cannot be satisfied, further refinement of the model is necessary to allocate manpower properly. In practical application, this additional constraint does not limit the applicability of the model as the typical number of days required to repair the total scope of damaged blades is much smaller than the total potential good weather days in a year. The need for this additional constraint was identified through the validation and testing process for the model; the model is valid for all other conditions within the scope of the analysis discussed in this paper.

When implementing the model in 5 sites in one region, the impact of incremental increased in manpower on total risk within that region can be clearly observed below in Figure 1, with the resulting generic risk within the region as the number of technicians changes from zero to four ranging between a risk coefficient scope of 108 to 0, with zero indicating that sufficient manpower exists to repair all damages within the region in 2012, therefore eliminating all risk for damage failures.

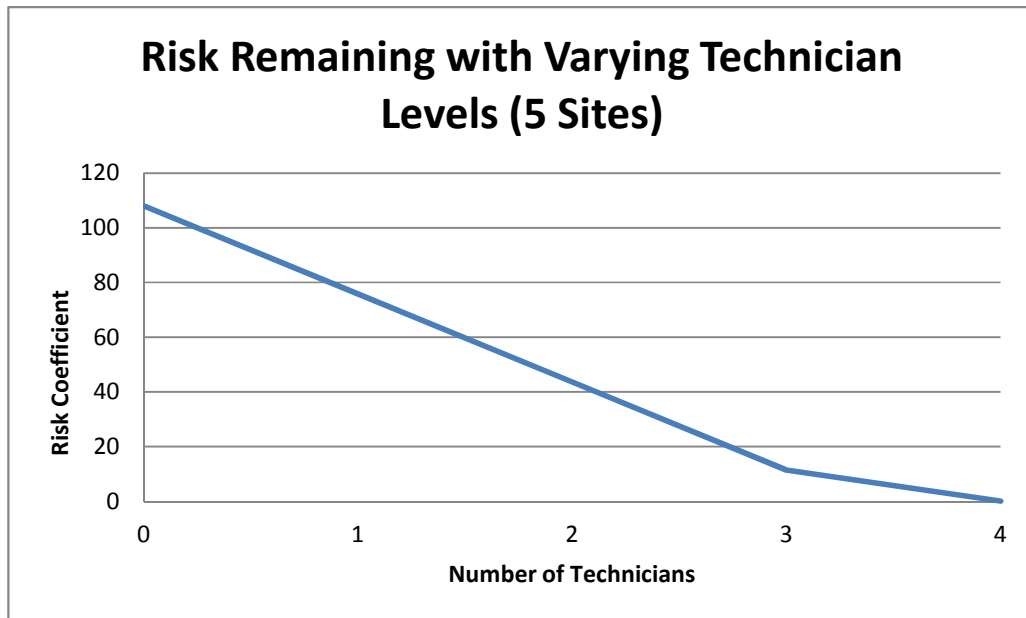


Figure 1. 5-Site Service Region Results

## Implications

While a generic “risk coefficient” may provide a barometer for the threats to an organization, the true value of a risk assessment is the assignment of a financial cost to that risk. The goal of this analysis was limited to only generically quantify the organizational risk associated with unrepaired blades as a function of blade repair technician headcount as an initial step in the analysis of the wind turbine service operations. With this accomplished, the costs associated with headcount increase, including salary, training, travel and overhead can now be included in the analysis and weighed against the cost of risk of blade failure discussed in this analysis. In this case, the organizational risk can be easily translated into a direct dollar figure associated with catastrophic failure of components by introducing a cost algorithm based on the risk calculation methodology. With this understanding, the service organization management can make an informed decision on “right sizing” the blade repair group based on the organizational risk tolerances and priorities of the organization. The approach utilized in this analysis can be used to establish an optimal performance level for a given headcount—this can be used as an ideal goal for the organization to measure actual performance against.

Additional financial analysis can be extended beyond this study. For example, the cost of lost work days associated with attempting to execute work during inoptimal times can be included in this analysis. Costs associated with allowing damages to degrade from one severity level to another, requiring additional repair time can be assessed. Lost wind turbine power production associated with extended repair times can be factored into this analysis. Costs associated with complete component failure and the likelihood of that failure can also be considered in this analysis. A sensitivity analysis can be performed to understand which of these factors are the most financially significant and a holistic repair strategy can be developed and modified based on the results.

## Next Steps

With the above model verified and implemented on a single service area consisting of 5 sites within a single region, the model can next be implemented across all service regions and all sites in the service fleet to quantify the entire operational risk of the North American fleet. Further data refinements and operational considerations should be included, such as technician vacation days, manpower hour efficiency considerations, travel time between sites for technicians and the financial links to risk discussed above. As a long term goal, stochastic

modeling of failure rates and damage propagation can be included in this analysis to consider the transient nature of blade damage and uncertainties associated with damage occurrences. It is clear that high value results can be obtained with both basic and complex modifications of the project scope defined herein. Additional key organizational stakeholders must be engaged to understand the potential applicability of this model within the blade repair functions as well as other service functions within the service organization.

## Conclusion

Integer programming provides a powerful method to evaluate and study complex systems. Key operational weaknesses and strengths can be assessed through evaluation of these complex system. By understanding the optimal targets for performance and operations, improvements can be developed and tracked against the ideal scenario. By understanding the constraints within an operational model and the effects of those constraints on the output of the operational model, decisions can be made to logically assess and modify those constraints that can be controlled by an organization to optimize operations.

## Acknowledgements

Our research team would like to acknowledge and thank Dr. Timothy Anderson, Opinder and Alex Nielsen for their support and contributions in developing and implementing the model discussed in this analysis in practice.

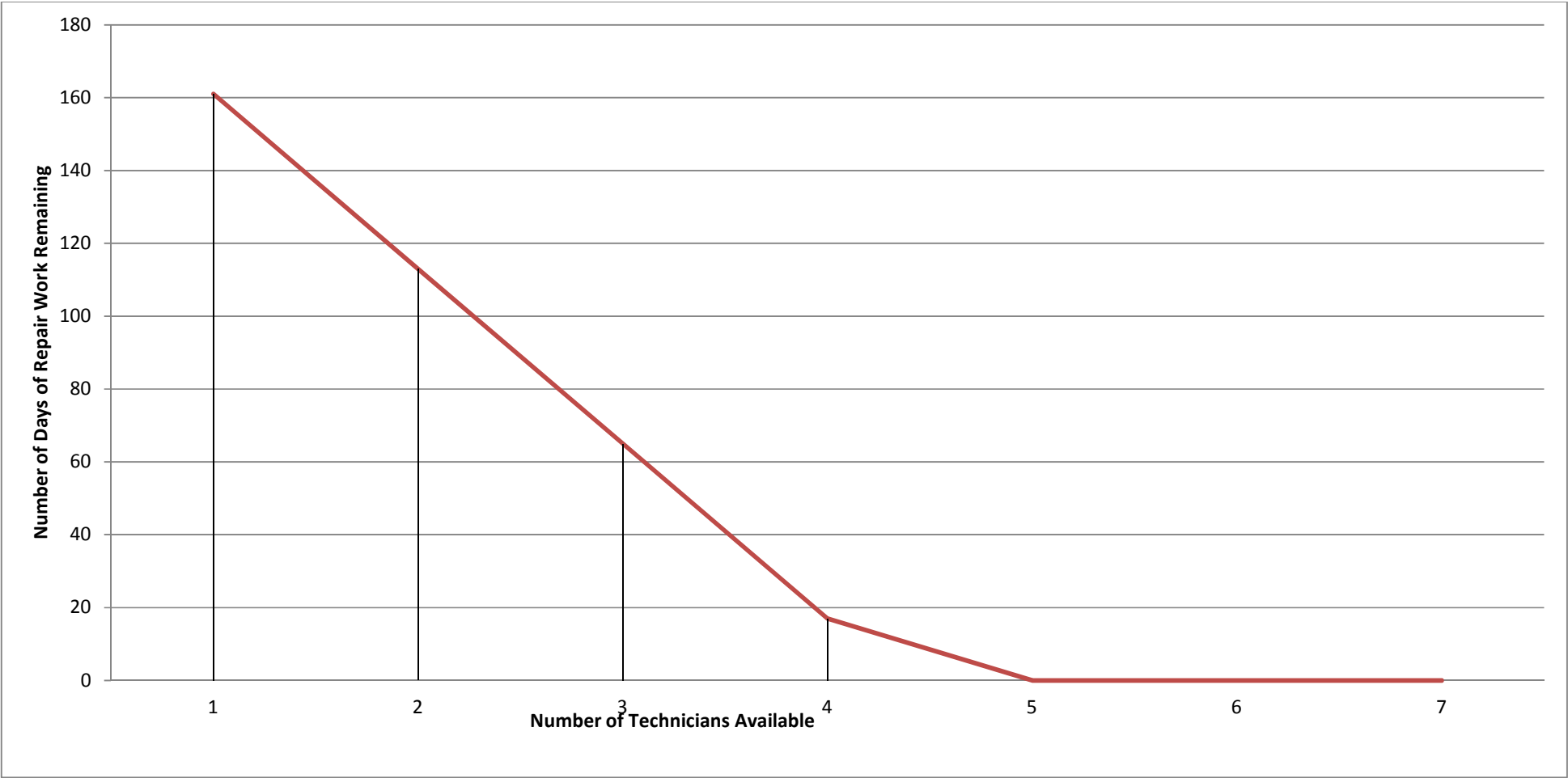
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Appendix I: Data

Site ID	Total Damages Recognize d to Date	Total Cat 3 Damag es	Total Cat 4 Damag es	Total Cat 5 Damag es	Number of Years Inspecte d	Typical Damages Per Year	Cat 3 (Assume 66% of total damages)	Cat 4 (Assume 25% of Total Damages)	Cat 5 (Assume 9% of total damages )	Total 2012 Cat 3 Damages	Total 2012 Cat 4 Damages	Total 2012 Cat 5 Damages	Customer Priority (1=Very Low, 4 = High)	Total Days of Repair Required	Total Risk Coefficient	Optimal Repair Window	Repair Window (Binary)												Days In Month In Work Window												
																	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec	
1	13	3	0	0	2	6.5	4	2	1	7	2	1	4	10	6	April Thru Sept	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	30	31	30	31	31	30	0	0	0
2	35	22	41	1	5	7	5	2	1	27	43	2	4	73	44	April Thru Sept	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	30	31	30	31	31	30	0	0	0
3	24	0	6	0	2	12	8	3	1	8	9	1	3	20	12	March thru Nov	0	0	1	1	1	1	1	1	1	1	1	0	0	0	31	30	31	30	31	31	30	31	30	0	
4	5	1	2	0	2	2.5	2	1	0	3	3	0	3	16	3	March thru Nov	0	0	1	1	1	1	1	1	1	1	1	0	0	0	31	30	31	30	31	31	30	31	30	0	
5	13	0	0	6	0.5	26	17	7	2	17	7	8	4	41	43	May Thru Sep	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
5	7	0	0	6	2	3.5	2	1	0	2	1	6	4	16	27	May Thru Sep	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
6	7	2	0	0	2	3.5	2	1	0	4	1	0	2	6	3	June Thru Sep	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	31	31	30	0	0	0	0		
7	1	0	1	0		1	1	0	0	1	1	0	1	2	1	June Thru Sep	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	30	31	31	30	0	0	0		
8	46	0	8	2	2	23	15	6	2	15	14	4	4	37	30	May Thru Sep	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
9	2	0	1	1	2	1	1	0	0	1	1	1	4	4	5	May Thru Sep	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
10	7	0	0	1	2	3.5	2	1	0	2	1	1	3	6	5	June Thru Sep	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	30	31	31	30	0	0	0		
11	12	1	1	0	2	6	4	2	1	5	3	1	3	9	5	June Thru Aug	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	30	31	31	0	0	0	0		
12	28	0	10	0	3	9.33333	6	2	1	6	12	1	3	20	13	May thru Oct	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	31	30	31	31	30	31	0	0	
13	12	0	4	0	2	6	4	2	1	4	6	1	4	11	7	May Thru Sep	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
14	1	1	0	0	2	0.5	0	0	0	1	0	0	4	2	1	July Thru Aug	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	31	31	0	0	0	0		
15	10	10	0	0	5	2	1	1	0	11	1	0	1	12	4	Jan thru Dec	1	1	1	1	1	1	1	1	1	1	1	1	1	31	28	31	30	31	30	31	31	30	31		
16	9	0	1	1	2	4.5	3	1	0	3	2	1	3	8	7	May Thru Oct	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	31	0	0	
17	4	0	0	1	2	2	1	1	0	1	1	1	2	4	3	June Thru Sep	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	30	31	31	30	0	0	0	
18	3	0	0	1	2	1.5	1	0	0	1	0	1	2	4	3	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
19	0	1	0	0	2	0	0	0	0	1	0	0	3	1	0	May Thru Oct	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	31	30	31	31	30	31	0	0	
20	6	2	2	0	2	3	2	1	0	4	3	0	3	7	4	May Thru Oct	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	31	30	31	31	30	31	0	0	
21	21	0	2	0	3	7	5	2	1	5	4	1	3	10	6	May Thru Oct	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	31	30	31	31	30	31	0	0	
22	12	0	0	1	2	6	4	2	1	4	2	2	3	9	7	June thru Aug	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	30	31	31	0	0	0	0		
23	5	0	1	0	2	2.5	2	1	0	2	2	0	3	4	2	June Thru Sep	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	30	31	31	30	0	0	0		
24	5	2	0	0	2	2.5	2	1	0	4	1	0	2	5	2	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
25	1	0	0	2	2	0.5	0	0	0	0	0	2	2	5	4	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
26	30	0	5	0	2	15	10	4	1	10	9	1	4	21	14	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
27	5	1	1	0	2	2.5	2	1	0	3	2	0	2	5	2	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	31	30	31	31	30	0	0	0
28	6	2	1	1	1	6	4	2	1	6	3	2	4	12	10	April thru Oct	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	30	31	30	31	31	30	31	0	
29	11	3	1	1	5	2.2	1	1	0	4	2	1	2	8	5	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
30	7	2	0	0	3	2.33333	2	1	0	4	1	0	3	5	2	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
31	3	0	0	1	2	1.5	1	0	0	1	0	1	2	4	3	June thru Aug	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	30	31	31	0	0	0	0	
32	15	1	1	0	2	7.5	5	2	1	6	3	1	4	10	7	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
33	6	1	0	0	2	3	2	1	0	3	1	0	4	4	3	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	31	30	0	0	0	
34	3	0	0	1	2	1.5	1	0	0	1	0	1	3	4	4	April thru Sept	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	30	31	30	31	31	30	0	0	0
35	23	88	12	15	2	11.5	8	3	1	96	15	16	3	143	89	Feb Thru Nov	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	28	31	30	31	30	31	31	30	31	
36	5	1	0	0	2	2.5	2	1	0	3	1	0	2	4	2	May thru Sept	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	31	30	31	31	30	0	0	0
37	2	1	0	0	2	1	1	0	0	2	0	0	2	2	1	May thru Sept	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	31	30	31	30	31	30	0	0	0
38	2	1	0	0	2	1	1	0	0	2	0	0	3	2	1	Mar thru Oct	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	31	30	31	30	31	31				



## Appendix II: GLPK code

```
1  /* Data Envelopment Analysis (DEA)
2  * Based on GLPK implementation by Sebastian Nowozin <nowozin@gmail.com>, DEA.MOD in GUSEK
3  * Original Example drawn from book, Productivity Measurement Using DEA by Tim Anderson:
4  * Modified for usage by Songphon M.
5  */
6
7  /* sets */
8  set TECHNICIANS;
9  set GOODWEATHERDAYS;
10 set SITES;
11
12 /* parameters */
13 param DAYSOFSITWORK {j in SITES};
14 param WORKABLEDAYS {j in SITES, k in GOODWEATHERDAYS};
15
16 /* decision variables: yi, i in {1,...,5}. yi = 1 -> technician i is assigned to a site i on day k*/
17 var y {i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} binary;
18 var RISKREDUCE {j in SITES, k in GOODWEATHERDAYS} binary;
19
20 /* objective function */
21 maximize z: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i,j,k];
22
23 /* Constraints */
24 s.t. WORKDAYCONSTRAINT: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i,j,k] <= sum{j in SITES} DAYSOFSITWORK[j];
25 s.t. WEATHERDAYS: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i,j,k] <= sum{j in SITES, k in GOODWEATHERDAYS} WORKABLEDAYS[j,k];
26
27 solve;
28
29
```

```
42 /*Define data sets*/
43 data;
44
45 /*define total number of technicians, etc*/
46 set TECHNICIANS := 1 2 3 4 5;
47 set GOODWEATHERDAYS := DayA DayB DayC DayD DayE;
48 set SITES := SITEA SITEB SITEC SITED SITEE;
49
50 /*define total days of work required in 2012 for each site*/
51 param DAYSOFSITWORK:=
52
53      SITEA  25
54      SITEB  1
55      SITEC  1
56      SITED  1
57      SITEE  1;
58
59 /*define total days that work can be performed*/
60 param WORKABLEDAYS: DayA DayB DayC DayD DayE:=
61
62      SITEA  1  1  1  1  1
63      SITEB  1  0  0  0  1
64      SITEC  0  1  0  0  1
65      SITED  0  0  0  0  1
66      SITEE  0  0  0  0  1;
67
68 ### SOLVE AND PRINT SOLUTION ###
69
70
71
72
73 end;
```

```

1  - /* Code for Final Group Project
2     ETM 540 Fall 2011
3     Wind Turbine Repair Problem */
4
5
6  /* sets */
7  set TECHNICIANS;
8  set GOODWEATHERDAYS;
9  set SITES;
10
11 /* parameters */
12 param DAYSOFSITWORK {j in SITES};
13 param WORKABLEDAYS {j in SITES, k in GOODWEATHERDAYS};
14 param NUMBEROFTECHNICIANS {i in TECHNICIANS};
15
16
17 /* decision variables: y[i, j, k], i in {1,...,5}, y[i, j, k] = 1 -> technician i is assigned to a site j on day k*/
18 var y {i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} binary;
19 var q integer;
20
21 /* objective function */
22 maximize z: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i, j, k];
23 minimize dev: q;
24 /* Constraints */
25 s.t. WORKDAYCONSTRAINT: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i, j, k] <= sum{j in SITES} DAYSOFSITWORK[j];
26
27 s.t. WEATHERDAYS: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i, j, k] <= sum{j in SITES, k in GOODWEATHERDAYS} WORKABLEDAYS[j, k];
28
29 /*THE BELOW CONSTRAINT IS MEANT TO PREVENT TECHNICIANS FROM WORKING ON MORE THAN ONE SITE IN A DAY*/
30 #AN...this does work. Nobody works at more than one site in a day. With nothing else going on...they all work at the same site.
31 s.t. Nosplitdudes{i in TECHNICIANS, k in GOODWEATHERDAYS}: sum{j in SITES} y[i, j, k] <= 1;
32
33 #s.t. RISKREDUCE{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS}: y[i, j, k] <= sum{i in TECHNICIANS} NUMBEROFTECHNICIANS[i];
34
35 #s.t. WEATHERDAYS: sum{i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} y[i, j, k] <= sum{j in SITES, k in GOODWEATHERDAYS} WORKABLEDAYS[j, k];
36
37 #constraint that spreads the work out among the guys.
38 s.t. eachthesamework{j in SITES}: sum{i in TECHNICIANS, k in GOODWEATHERDAYS} y[i, j, k] <= q;
39 /*new constraint because only the above constraint does not give correct answer*/
40
41
42 solve;
43
44 printf "SITE\n";
45 for {j in SITES} {
46     # printf "\n", j, DAYSOFSITWORK[j];
47     printf "%s\t%1.2f\n", j, DAYSOFSITWORK[j];
48 }
49
50 printf "SITE\n";
51 for {i in TECHNICIANS, j in SITES, k in GOODWEATHERDAYS} {
52     # printf "\n", j, RISKREDUCE[j];
53     printf "%s\t%1.2f\n", j, y[i, j, k];
54 }
55
56
57 /*Define data sets*/
58 data;
59
60 /*define total number of technicians, etc*/
61 set TECHNICIANS := 1 2 3 4 5 6 7 8 9 10;
62 set GOODWEATHERDAYS := Day1 Day2 Day3 Day4 Day5 Day6 Day7 Day8 Day9 Day10 Day11 Day12 Day13 Day14 Day15 Day16
63     Day17 Day18 Day19 Day20 Day21 Day22 Day23 Day24 Day25 Day26 Day27 Day28 Day29 Day30 Day31 Day32 Day33
64     Day34 Day35 Day36 Day37 Day38 Day39 Day40 Day41 Day42 Day43 Day44 Day45 Day46 Day47 Day48 Day49 Day50 Day51
65     Day52 Day53 Day54 Day55 Day56 Day57 Day58 Day59 Day60 Day61 Day62 Day63 Day64 Day65 Day66 Day67 Day68
66     Day69 Day70 Day71 Day72 Day73 Day74 Day75 Day76 Day77 Day78 Day79 Day80 Day81 Day82 Day83 Day84 Day85 Day86
67     Day87 Day88 Day89 Day90 Day91 Day92 Day93 Day94 Day95 Day96 Day97 Day98 Day99 Day100 Day101 Day102 Day103
68     Day104 Day105 Day106 Day107 Day108 Day109 Day110 Day111 Day112 Day113 Day114 Day115 Day116 Day117 Day118 Day119 Day120 Day121
69     Day122 Day123 Day124 Day125 Day126 Day127 Day128 Day129 Day130 Day131 Day132 Day133 Day134 Day135 Day136 Day137 Day138

```



[illegible]

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