DSS FOR AFTERMARKET SERVICES

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MOTIVATION

Additive manufacturing has become a technology that has been developing rapidly in the last 20 years and used by many industries. GE Additive is one of the world-leading companies in the additive manufacturing sector. Arcam EBM is a sub-business of GE Additive and it is one of the leading companies in the additive manufacturing sector with the Electron Beam Melting technology. Today, the company have more than 350 systems been installed world-wide with almost 200 customers globally. Arcam EBM is also providing aftermarket services to the customers.

There are field-service engineers (FSEs) constitute aftermarket services. Since the industry is relatively new, and there are only several FSEs for aftermarket services, the decision to allocate FSEs to customer sites has become very important. In addition, since customers are from critical sectors such as the aviation and the healthcare industry, the failure of their machines can result in high losses. Apart from the FSEs to be capable of maintenance services, it is necessary to respond quickly to machine failure problems and preventive maintenance of machines needs to be done on time. Furthermore, FSEs need to spend more time in the customer site and, it is expected that FSEs will spend most of their total annual working time in the customer site. For this purposes, travel times should be reduced as much as possible. Thus, a decision support system with a long-term tolerance, including strategic level decisions, is required.

PROBLEM DEFINITION

In order to increase the effectiveness of management of aftermarket services, there are several factors to improve such as response time to the customer site, travel time spent to provide services, and utilization of FSEs. According to the company, the travel time consumes a great proportion of total yearly working hours of FSEs, it is more desired for FSEs to spend more time with customers. Considering all these factors an insight providing tool is needed for the allocations of field service engineers, tracking the aftermarket service operations and locating new hired FSEs. Therefore, our goal is to develop a decision support system which has an robust optimization model that minimizes travel time, balance workloads to FSEs, reduce the response times to service demands in order to give insights to strategic level decisions.

METHODOLOGY

The aim of the project is to generate a decision support system (DSS) that is used for location and allocation decisions of current and possible new hire field service engineers (FSE). DSS includes a robust optimization model that gives best solution considering many different cases could happen in a year, under high uncertainty of customer demands for machine failures.

General Structure of Decision Support System

The general structure of the Decision Support System has components, the first part is called as interface, where the basic data is inserted and edited on Excel. This part includes engineer names, locations, customer names, locations, machines that customers have, the coordinates of customers and engineers inserted. We generated a basic Excel format for the company in order to give them flexibility and maintenance easiness.

The second part is data generation and modeling part, this section is not seen or used by decision maker in general use. The data generation is where the algorithms were coded to generate the input of the model. They are the land travel distance, land travel duration, flight distance, flight duration, yearly preventive maintenance visits for each machine, corrective maintenance visits (populated using probabilities), scenario generations, scenario selections, response time data and so on. These populated data are kept in Excel as the database part, and some are not written in the database but only on generated on Python for the model purposes. The model is embedded in this system to be run when the data generation is ready. It is a multi-objective scenario based robust optimization model that locates FSEs to possible locations and allocates them to yearly visits for 10 different scenarios in order to minimize travel time, response time to the customer site, and to balance the workload of FSEs. The last part is where the output generated and evaluated using Tableau, we call it as the second part of the interface since that is the most important part for decision maker to spend time to get insights about yearly, monthly visits, FSE workloads, total travel time per FSE, response time to the customer site and many other important KPI to analyze their business activities better.

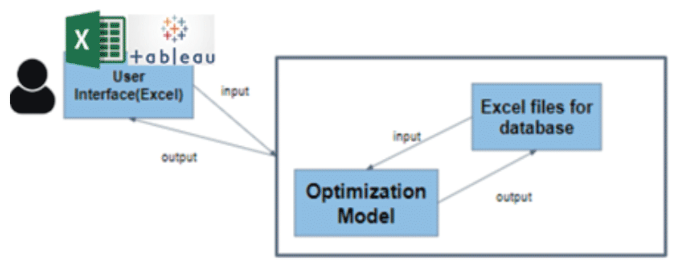


Figure 1. General View of the Decision Support System

Scenario Based Optimization

In many optimization models, it is assumed that the data related to the problem are known precisely. However, this situation is not very common in practice. Actual data are subject to uncertainty due to their randomness, measurement errors or other reasons. Since the solution of an optimization problem generally shows high sensitivity to data changes, it is necessary not to ignore data uncertainty. Robust optimization is an important methodology used in the solution of optimization problems with data uncertainty. The main reason for choosing Robust optimization is that in many models it can be used for situations where parameters are uncertain or distributions are unknown. Models that do not care about the uncertainties in the data provide optimization for the problems with a single scenario according to certain assumptions. However, solutions made according to a single scenario will lose their effectiveness in case of different situations that may occur in the future. Models prepared according to a large number of scenarios can cover future situations and these models have a flexible solution.

Application of the Scenario Based Robust Optimization

The aim of our problem is not to specifically to assign people to visits when case occurs, or schedule tasks to them weekly or daily, the aim is to make decisions for locating the FSEs, or hiring new FSEs and locating them in correct locations, so that when cases occur in the future, the capacity would be enough, the FSEs could provide services as early as possible and minimize the travel time.

As it is understood from those objectives, they are strategic and insight oriented, and the model should find a solution that would satisfy expectations of decision maker for future "possible cases", also it should give ideas about the future workloads, and demands in average. Yet, these cases could vary, a lot since the failure demands are probabilistic, and it could seem like a stochastic programming problem in which the expected of the demands are calculated and solved. In our case, to reach the expected demand would take years considering the model would be run only couple of times in a year. There are several different methods for robust optimization and conservativeness of the models have been discussed by researchers for many years, because if we could consider way unlikely worse cases (high visit demands in our case), the model will be too weak and would be away from optimum for giving importance to those unlikely cases. In addition to that, it is very difficult to solve optimization problems for thousands of scenarios computationally, and there has to be some methods to reduce the number of cases to solve them in computers in reasonable timescales. What we have observed from the literature is that many of the methods that are claimed as successful ways of selecting representative "subsets", yet considering the complexity of location allocation problem there has be a more practical solution to find representative scenario set.

Pseudo Code for Scenario Selection

```
-Generate 10000 scenarios using probabilities of failures
- Calculate E(x) for total visits in a year for all scenarios
- Calculate σ of all scenarios for total visits in a year
- For all scenarios generated:
        low_values[ ] -> if total visits of scenario between E(x) - 2σ and E(x) - σ
                lowlist -> select rand (2,4) of low_values[ ]
                high_values[ ] -> if total visits of scenario between E(x) +σ and E(x) +2σ
                highlist -> select rand (2,4) of high_values[ ]
midvalues[ ] -> if total visits of scenario between E(x) +-σ
midlist <- select (10 - count of highlist - count of lowlist ) of midvalues[ ]
        return selectedscenarios ⊠ highlist + lowlist + midlist
```

Analysis of Scenario Selection

We expected averages of means of selected subsets (each consist of 10 scenario) would converge to the population mean, therefore, we repeated the experiment of scenario selection for 1000 times and plotted the differences of averages of subset, and the expected population mean, all are calculated for total number of tasks that could happen in a year. It may not cover and represent entire population, yet we could come up with an idea that includes "edge" case that are likely but not very close to means by using this method, which could be very useful and practical for business uses to obtain meaningful insights.

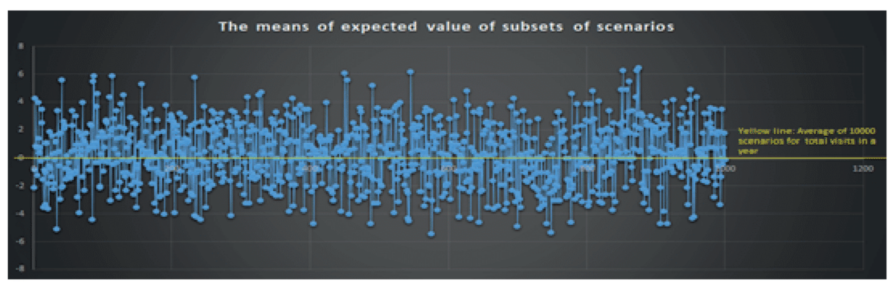


Figure 2. The graph of the differences of averages of subsets generated for 1000 trials

As the graph in figure 2 shows the averages of subsets are close to expected population even the fluctuations do not exceed +-6, this fluctuation could be acceptable and shows variability of the subsets (samples).

Proposed Model

We are trying to develop our mathematical model to assign FSEs to customer sites for any given scenarios, under the uncertainty. It is a multi-objective model that considers travel time and work balance of FSEs and response times. The model is scenario based, and it is created to solve the best solution considering the total travel times, total response times and maximum FSE load in all scenarios, and minimize the maximum of these three components. Therefore, we set an upper limit for the total travel times, total response times and maximum FSE load searching in all scenarios.

Since the aim is to find optimum location of FSEs, and allocation of tasks to the FSEs, we used network approach to represent each visit. There are nodes that represent any separated visit to the customers, and there might be several nodes (tasks) for any customer. In the mathematical model we propose, the required visits set j represents this tasks that could be assign to any FSE, based on the decision variable of Xijms, which is the decision of allocation of j task to an FSE i in month m and scenario s. The parameter months is needed for tracking the month limits, since an engineer (FSE) can work at most 40 hours in a week, and since there are month requirement for tasks to be completed, it is a restriction that some tasks might not be given to a FSE due to monthly workload capacity. The parameter Travelij shows the travel time spent from location of FSE i to the customer location of task j. Since FSEs are currently in different locations, travel time differs from FSE to FSE even for same customer. In the set i, the first 10 FSE are currently working, and there are 10 more FSE locations that could be new hires, so the scalar parameter AllowF-SE (maximum number of FSE that could work) shows that there could be x FSEs working This parameter is used for the decision of Yi which represents if FSE i is located or not. The parameter named Month (j,m) shows the timely cost of responding task j in month m, which increases when responding much later than required response time and worsens the objective function.

Parameters

$Travel_{ij}$	The travel time of each FSE i at each visit j
$Service_{j}$	The service time spent on visit j
$Month_{jm}$	1 if the task j is needed to be completed in month m, 0 otw
$Skills_{ij}$	1 if FSE i is allowed to be assigned to task j, 0 otherwise
$Senario_{js}$	1 if task j is in scenario s
MonthLimit	Maximum load in a month
AllowFSE	Number of FSEs allowed to assign tasks

Decision Variables

X_{jms}	1 if FSE i is assigned to visit j, in month m, in scenario s, 0 oth.
Y_{i}	1 if FSE i is working (hired currently working), 0 oth.
$Load_{is}$	Total load for each FSE i in scenario s
Up_{s}	Upper limit for FSE loads in scenario s
UpMax	Upper bound of FSE loads for all scenarios
$totaltravel_{s}$	Total time spent on travel by all FSEs in scenario s
totaltravelMax	Upper bound of total travel times for all scenarios
$totalresponse_{s}$	Total time based response in scenario s
totalresponseMax	Upper bound of total response times for all scenarios

Objective Function

$$z^{*} = \text{minimize } w1 * UpMax + w2 * totaltravelMax + w3 * totalresponseMax \quad (1)$$

Constraints

$$UpMax \geq Up_{s} \quad , \forall_{is} \quad (2)$$

$$Up_{s} \geq Load_{is} \quad , \forall_{is} \quad (3)$$

$$totalresponseMax \geq \sum_{s} totalresponse_{s} \quad (4)$$

$$totaltravelMax \geq \sum_{s} totaltravel_{s} \quad (5)$$

$$Load_{is} = \sum_{jm} (Travel_{ji} + Service_{j}) * X_{jms})), \quad \forall_{is} \quad (6)$$

$$totaltravels = \sum_{ij} (Travel_{ji} * X_{ijms}) \quad (7)$$

$$totalresponses = \sum_{ijm} (Month_{jm} * X_{ijms}) \quad (8)$$

$$\sum_{im} X_{ijms} = Scenario_{js} \quad , \forall_{is} \quad (9)$$

$$X_{ijms} \leq Y_{i} * Skills_{ij} \quad , \forall_{ijms} \quad (10)$$

$$Y_{i} = 1 , \quad \text{for } i \leq 10 \quad (11)$$

$$\sum_{i} Y_{i} \leq AllowFSE \quad (12)$$

$$\sum_{jm} (Month)_{jm} * X_{ijms} * (Travel_{ji} + Service_{j}) \leq MonthLimit \quad , \forall_{ims} \quad (13)$$

$$X_{ijms} \in \{0 ,1\} \quad , \forall_{ijms} \quad (14)$$

$$Y_{i} \geq 0 \quad , \forall_{i} \quad (15)$$

RESULTS

After the data generation process, model input file is generated for optimization model. New hired FSEs are also considered in order to give insights to company. The output of model is generated using Python and exported to Excel files as the tables later posted on dashboards using Tableau are shown as follows.

Table 1. Located FSEs are allocated to tasks in given months

Scenario	Task ID	Customer	Machine Type	Service Type	Service Time	Month	Service Time Minutes	FSE	Task ID2	Month visited	Difference of month
1	1	CUS-US026	Mach. Type A	PM	20	5	1200	FSE-US001	1	6	-1
1	2	CUS-US024	Mach. Type A	PM	20	3	1200	FSE-US001	2	2	1
1	3	CUS-US002	Mach. Type A	PM	56	9	3360	FSE-US009	3	10	-1
1	4	CUS-US022	Mach. Type A	PM	12	1	720	FSE-US001	4	1	0
1	5	CUS-US045	Mach. Type A	PM	12	10	720	FSE-US007	5	10	0
1	6	CUS-US024	Mach. Type A	PM	12	11	720	FSE-US001	6	11	0
1	7	CUS-CA003	Mach. Type A	PM	36	6	2160	FSE-US001	7	7	-1
1	8	CUS-US002	Mach. Type A	PM	48	10	2880	FSE-US009	8	10	0
1	9	CUS-US008	Mach. Type A	PM	24	12	1440	FSE-US009	9	11	1
1	10	CUS-US009	Mach. Type A	PM	16	6	960	FSE-US001	10	7	-1

Table 2. Located FSEs are allocated to tasks in given months (2 more hire case)

Scenario	Task ID	Customer	Machine Type	Service Type	Service Time	Required Visit Month	Service Time Minutes	FSE	Task ID2	Month visited	Difference of month
1	1	CUS-US026	Mach. Type A	PM	20	5	1200	NEW-FSE-3	1	6	1
1	2	CUS-US024	Mach. Type A	PM	20	3	1200	NEW-FSE-3	2	3	1
1	3	CUS-US002	Mach. Type A	PM	56	9	3360	FSE-US009	3	8	1
1	4	CUS-US022	Mach. Type A	PM	12	1	720	FSE-US001	4	1	1
1	5	CUS-US045	Mach. Type A	PM	12	10	720	FSE-US007	5	10	1
1	6	CUS-US024	Mach. Type A	PM	12	11	720	NEW-FSE-3	6	12	1
1	7	CUS-CA003	Mach. Type A	PM	36	6	2160	FSE-US001	7	7	1
1	8	CUS-US002	Mach. Type A	PM	48	10	2880	FSE-US009	8	10	1
1	9	CUS-US008	Mach. Type A	PM	24	12	1440	FSE-US009	9	12	1
1	10	CUS-US009	Mach. Type A	PM	16	6	960	FSE-US001	10	7	1

The post processed outcomes which are determined as the KPIs of the aftermarket service managements are as follows:

- Total travel time of FSEs
- Total time spent at customer site of FSEs
- Total workload of FSEs
- Total number of visits
- Total number of on time visits in a year
- Workload share of FSEs per machine type
- Occupied FSEs (utility levels)

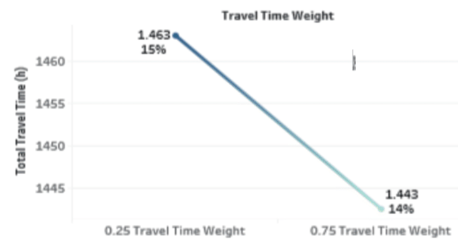
Travel Time

Following dashboard shows travel time analysis with respect to machines, FSEs an

ServiceType	Required Customer Site Time (h)	# of Total Visits
Corrective Maintenance	5.360	136
Preventive Maintenance	2.572	101
Installation	640	15
Grand Total	8.572	252

Travel Time Share (%)	Customer Site Time Share (%)	Total WorkLoad(h)
14,5%	85,5%	10.025

Travel Time Variation



FSE Travel Time Share - Year

FSE	Total WorkLoad(h)	Customer Site Time Share (%)	Travel Time Share (%)
FSE7	1.076	80,9%	19,1%
FSE4	1.073	83,3%	16,7%
FSE3	1.055	83,8%	16,2%
FSE10	951	83,9%	16,1%
FSE1	1.073	84,0%	16,0%
FSE2	1.003	85,1%	14,9%
FSE6	820	85,6%	14,4%
FSE9	997	87,7%	12,3%
FSE8	998	89,6%	10,4%
FSE5	968	93,0%	7,0%
Grand Total	1.001	85,7%	14,3%

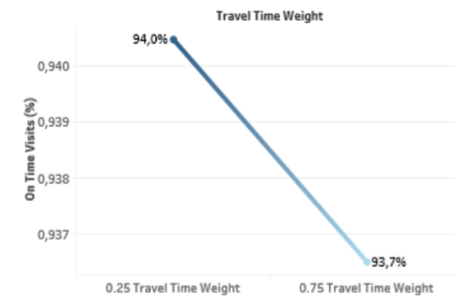
Machine Type Travel Time Share - Year

MachineType	Total WorkLoad(h)	Customer Site Time Share (%)	Travel Time Share (%)
Mach. Type - D	1.401	81,5%	18,5%
Mach. Type - B	2.475	84,4%	15,6%
Mach. Type - A	3.454	85,5%	14,5%
Mach. Type - C	1.716	85,8%	14,2%
Mach. Type - E	969	94,5%	5,5%
Grand Total	2.003	86,3%	13,7%

On Time Visits

Similar to travel time analysis, on time visits results are as follows with respect to machine type, FSEs and service types.

Rate of "On Time" Visits



On Time Visits (%)	# of On Time Visits	# of Total Visits
92,9%	234	252

FSE- On Time Visits

FSE s	On Time FSE Visits (%)	# of On Time Visits	# of Total Visits
FSE7	100%	20	20
FSE8	100%	27	27
FSE10	96%	22	23
FSE1	94%	32	34
FSE4	94%	32	34
FSE5	92%	22	24
FSE2	89%	17	19
FSE6	89%	16	18
FSE3	88%	23	26
FSE9	85%	23	27

On Time Visits - Machine Type

MachineType	On Time Mach. Visits (%)	# of On Time Visits	# of Total Visits
Mach. Type - A	96%	74	77
Mach. Type - B	95%	61	64
Mach. Type - C	96%	50	52
Mach. Type - D	86%	32	37
Mach. Type - E	86%	19	22

Total # of FSEs
10FSE

FSE Visits and Utility

Compnay is able to track the utility of FSEs with respect to total time available in a year and machine type. Monthly visit views are also provided.

Yearly FSE Utility Level

FSE	Total WorkLoad(h)	FSE Utility Level (%)
FSE7	1.076	89,7%
FSE1	1.073	89,4%
FSE4	1.073	89,4%
FSE3	1.055	87,9%
FSE2	1.003	83,6%
FSE8	998	83,1%
FSE9	997	83,1%
FSE5	968	80,7%
FSE10	951	79,2%
FSE6	820	68,4%
Grand Total	1.001	83,5%

Mach. Type - FSE Load Share

	MachineType				
FSE	Mach. Type - A	Mach. Type - B	Mach. Type - C	Mach. Type - D	Mach. Type - E
FSE1	7%	11%	9%	11%	22%
FSE2	17%	13%	4%	3%	3%
FSE3	5%	12%		45%	
FSE4	18%	10%	9%		3%
FSE5	4%	3%	10%		59%
FSE6	15%	1%	14%	1%	
FSE7	5%	20%	6%	21%	
FSE8	7%	7%	25%	6%	8%
FSE9	16%	13%	1%	7%	
FSE10	8%	9%	22%	7%	4%
Grand Total	100%	100%	100%	100%	100%

FSE Monthly Visits

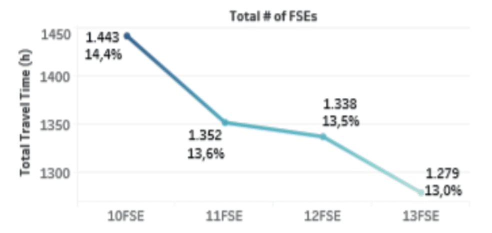
Total # of FSEs
10FSE

	Assigned Month										
FSE	Jan	Feb	Mar	Apr	May	Jun	Aug	Sep	Oct	Nov	Dec
FSE1	3	3	6	2	1	5	5	4	2	3	
FSE2	2		2		2		2	3	3	3	2
FSE3		2			4	5	2	3	3	3	4
FSE4	5	5	1	1		6	2	2	6	3	3
FSE5	2	1		1	1	3	3	1	3	6	3
FSE6	2	2	1			1	1	2	3	4	2
FSE7	5	1	3	1	2		2	2	2	2	
FSE8	4	2				9	1	2	3	1	5
FSE9	4		1	3	3	1	2	4	3	3	3
FSE10	2	3				3	5	2	4	2	2
Grand Total	29	19	14	8	13	33	25	25	32	30	24

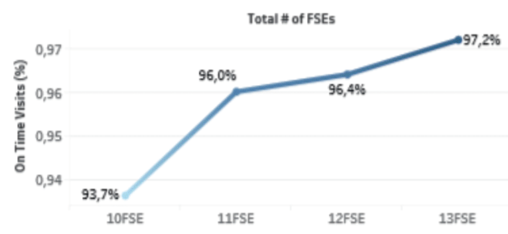
Hired FSE Analysis

The analysis below would be helpful while giving hiring FSE decision. The graphs and tables shows how the system will be affected when a new FSE is hired.

Travel Time - Total # of FSEs



On Time Visits - Total # of FSEs



On Time Visits- Machine Type- Total # of FSEs

	Total # of FSEs			
MachineType	10FSE	11FSE	12FSE	13FSE
Mach. Type - A	74	74	75	75
Mach. Type - B	61	63	62	63
Mach. Type - C	50	50	50	51
Mach. Type - D	32	36	36	36
Mach. Type - E	19	19	20	20

Utility Level of FSEs in a Year - Total # of FSEs

	Total # of FSEs			
FSE	10FSE	11FSE	12FSE	13FSE
FSE3	87,9%	81,3%	73,9%	69,7%
FSE7	89,7%	77,1%	76,4%	63,3%
FSE1	89,4%	78,3%	72,1%	66,0%
FSE4	89,4%	76,7%	69,8%	63,5%
FSE10	79,2%	79,8%	70,9%	67,9%
FSE9	83,1%	77,9%	67,5%	63,6%
FSE2	83,6%	72,1%	68,1%	61,3%
FSE5	80,7%	74,2%	67,2%	61,1%
FSE8	83,1%	70,5%	67,0%	60,5%
FSE6	68,4%	61,7%	52,1%	45,8%
FSE14		77,6%	66,8%	65,5%
FSE15			74,1%	
FSE13				69,0%
FSE19				63,8%
Grand Total	83,5%	75,2%	68,8%	63,1%

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