

THE AUSTRALIAN NATIONAL UNIVERSITY



FACULTY OF ENGINEERING AND INFORMATION
TECHNOLOGY

PREDICTIVE MAINTENANCE IN A
TELECOMMUNICATION NETWORK

Daryl Raymond Read

April, 2000

A thesis submitted for the degree of Master of Engineering
of The Australian National University.

Declaration

This thesis contains no material which has been previously accepted for the award of any other degree or diploma in any university, institute or college, and contains no material previously published or written by another person, except where due reference is made.

Canberra, March 2000.



Daryl Read

Department of Engineering
Faculty of Engineering and Information Technology

The Australian National University

Canberra ACT 0200

Australia

Acknowledgements

There are many people that I would like to thank for their support of my work.

Firstly I would like to thank Dr Brennan McCarragher for his patience and understanding. I am very grateful for the confidence, support, knowledge and friendship he has so generously shared during my time at the ANU.

I would also like to thank Wendy for being so supportive. I could not have done this without her friendship, love and understanding.

A big thanks to Mum, Dad, Wayne and Brendan for supporting my decisions and providing a strong and encouraging foundation for me to grow.

Thanks also to David Aitken, John Clark, Murray Blackwell and Graham Stockwell for being so unselfish with their time and knowledge. Also thank you to Telstra for their financial support.

Finally, thank you to Barry Newell, Josephine Farmer, Sharon Goddard, Sue Cameron, Paul Stacy, Ying Guo, Zisi Liu, and Paul Malcolm for their friendship, advice and help over the past two years.

Abstract

This thesis is motivated by the need to explore more effective ways of maintaining a telecommunications network. Specifically we study a predictive maintenance approach that predicts which network problems customers will report in the future. To determine the operating conditions required to successfully operate a predictive maintenance scheme Telstra's customer access network (CAN) maintenance system has been analysed and modelled as a stochastic discrete event queuing network.

An analysis of fault marked (FM) and fault blocked (FB) data to determine its suitability for predictive maintenance is presented. This analysis determines the percentage of FM/FB lines that correctly predict future customer trouble reports (TRs) (denoted the predictive power) and examines the ability of certain FM/FB characteristics to increase predictive power. The percentage of the mean daily TR volume that is predicted, and could possibly be prevented, is calculated along with the distributions of the delay between a FM/FB arrival and the arrival of the TR it predicts. In an attempt to explain the low predictive power of FB lines an analysis into the consistency of FB lines is conducted. We also examine the relationship between the number of times a line is FB and its predictive power.

Telstra's CAN maintenance system model is simulated to determine the requirements of FM/FB data such that a predictive maintenance scheme could be used to improve the system's performance. System performance is evaluated by four performance measures: i) customer trouble report (TR) volume; ii) mean TR system time; iii) maintenance workload; and iv) number of TRs that miss a predefined system time cut-off. These measures are used to compare the performance of the model under different operating conditions.

It is shown that if Telstra is unable to identify which TRs are predicted by which FM/FBs a minimum mean of two TRs must result from a single FM/FB before all performance measures are reduced below their current levels. When the mean number of TRs per FM/FB is two, a FM/FB maintenance priority scheme is the best priority scheme reducing all performance measures with a minimum predictive power of 58%.

If Telstra is able to identify the TRs that are predicted by each FM/FB, when a mean of two TRs result from a single FM/FB, a No Priority maintenance scheme reduces all performance measures with a minimum predictive power of 51%.

To reduce the mean TR system time and to reduce the number of times Telstra miss a customer service guarantee (CSG) repair time an Estimated Time to Fix (ETF) Priority scheme is introduced. We show that with a system cut-off time of 16 hours the ETF Priority scheme is able to reduce all performance measures with a minimum predictive power of 50%. It is shown that this scheme is able to reduce the number of TRs that have a system time greater than 16 hours by approximately 87%. We also investigate the sensitivity of system performance to variations in the cut-off time and discover that it is insensitive for predictive powers greater than 60%. At predictive powers below 60% the preferred system time cut-off will be a compromise between a small system time cut-off and reducing the number of TRs that miss a cut-off.

Glossary of terms

ACE	Alarm Correlation Engine. Developed by GTE and discussed in [24].
AI	Artificial Intelligence.
ANSS	Access Network Support System. Used by British Telecom and discussed in [17].
APCAMS	Automatic Pressurised Cable Monitoring System. Used by Telstra and discussed in [9].
AXE	Exchanges produced by Ericsson that report Fault Marked and Fault Blocked data.
BT	British Telecom.
C&C	Commercial and Consumer. A division of Telstra that are responsible for the customer access network (CAN).
CAN	Customer Access Network. The part of the network between an exchange and a customer's premises.
CANES	Customer Access Network Evaluation Scheme. Used by Telstra and discussed in [11].
CLIQ Test	Customer Line Insulation Quality Test.
CPE	Customer Premises Equipment.
CSG	Customer Service Guarantee.
DES	Discrete Event System.
DIRECTOR	System which automates the programming and despatch of work to the field staff.
ETF	Estimated Time to Fix. A type of maintenance priority scheme based on the estimated time to fix UTR faults.
FB	Fault Blocked. A customer line that has an insulation resistance equal to or less than 20 k Ω .

FieldMATE	Field Mobile Access Terminal Equipment.
FIFO	First In First Out. A type of queuing priority scheme.
FM	Fault Marked. A customer line that has an insulation resistance greater than 20 k Ω but equal to or less than 50 k Ω .
FM/FB	Both Fault Marked and Fault Blocked.
GAs	Genetic Algorithms.
GTE	General Telephone and Electric. A global telecommunications company.
IEN	Inter Exchange Network. The cable that connects Telstra's exchanges.
INE	Intelligent Network Element. Discussed by Pierce in [14].
LIFO	Last In First Out. A type of queuing priority scheme.
MDF	Main Distribution Frame. The boundary point between an exchange and the customer access network (CAN).
NBP	Network Boundary Point. The boundary between the CAN and the customer premises equipment (CPE). Usually defined as the first telephone socket on a customer's premises.
NTG	Network and Technology Group. A division of Telstra that is responsible for the maintenance of exchanges and the inter exchange network.
PTR	Predictable Trouble Report. A TR that has been predicted by FM/FB data.
QoS	Quality of Service.
TADS	Testing And Diagnosis Server. Contains the database that stores FM/FB data once it has been downloaded from AXE exchanges.
ToW	Ticket of Work.
TR	Trouble Report. A customer reported fault.

UTR

Unpredictable Trouble Report. A TR that had not been predicted by FM/FB data.

1. The first instance of trouble occurred at 10:00 a.m.
2. The second instance of trouble occurred at 11:00 a.m.
3. The third instance of trouble occurred at 12:00 p.m.
4. The fourth instance of trouble occurred at 1:00 p.m.
5. The fifth instance of trouble occurred at 2:00 p.m.
6. The sixth instance of trouble occurred at 3:00 p.m.
7. The seventh instance of trouble occurred at 4:00 p.m.
8. The eighth instance of trouble occurred at 5:00 p.m.
9. The ninth instance of trouble occurred at 6:00 p.m.
10. The tenth instance of trouble occurred at 7:00 p.m.
11. The eleventh instance of trouble occurred at 8:00 p.m.
12. The twelfth instance of trouble occurred at 9:00 p.m.
13. The thirteenth instance of trouble occurred at 10:00 p.m.
14. The fourteenth instance of trouble occurred at 11:00 p.m.
15. The fifteenth instance of trouble occurred at 12:00 a.m.
16. The sixteenth instance of trouble occurred at 1:00 a.m.
17. The seventeenth instance of trouble occurred at 2:00 a.m.
18. The eighteenth instance of trouble occurred at 3:00 a.m.
19. The nineteenth instance of trouble occurred at 4:00 a.m.
20. The twentieth instance of trouble occurred at 5:00 a.m.
21. The twenty-first instance of trouble occurred at 6:00 a.m.
22. The twenty-second instance of trouble occurred at 7:00 a.m.
23. The twenty-third instance of trouble occurred at 8:00 a.m.
24. The twenty-fourth instance of trouble occurred at 9:00 a.m.
25. The twenty-fifth instance of trouble occurred at 10:00 a.m.
26. The twenty-sixth instance of trouble occurred at 11:00 a.m.
27. The twenty-seventh instance of trouble occurred at 12:00 p.m.
28. The twenty-eighth instance of trouble occurred at 1:00 p.m.
29. The twenty-ninth instance of trouble occurred at 2:00 p.m.
30. The thirtieth instance of trouble occurred at 3:00 p.m.
31. The thirty-first instance of trouble occurred at 4:00 p.m.
32. The thirty-second instance of trouble occurred at 5:00 p.m.
33. The thirty-third instance of trouble occurred at 6:00 p.m.
34. The thirty-fourth instance of trouble occurred at 7:00 p.m.
35. The thirty-fifth instance of trouble occurred at 8:00 p.m.
36. The thirty-sixth instance of trouble occurred at 9:00 p.m.
37. The thirty-seventh instance of trouble occurred at 10:00 p.m.
38. The thirty-eighth instance of trouble occurred at 11:00 p.m.
39. The thirty-ninth instance of trouble occurred at 12:00 a.m.
40. The fortieth instance of trouble occurred at 1:00 a.m.
41. The forty-first instance of trouble occurred at 2:00 a.m.
42. The forty-second instance of trouble occurred at 3:00 a.m.
43. The forty-third instance of trouble occurred at 4:00 a.m.
44. The forty-fourth instance of trouble occurred at 5:00 a.m.
45. The forty-fifth instance of trouble occurred at 6:00 a.m.
46. The forty-sixth instance of trouble occurred at 7:00 a.m.
47. The forty-seventh instance of trouble occurred at 8:00 a.m.
48. The forty-eighth instance of trouble occurred at 9:00 a.m.
49. The forty-ninth instance of trouble occurred at 10:00 a.m.
50. The fiftieth instance of trouble occurred at 11:00 a.m.
51. The fifty-first instance of trouble occurred at 12:00 p.m.
52. The fifty-second instance of trouble occurred at 1:00 p.m.
53. The fifty-third instance of trouble occurred at 2:00 p.m.
54. The fifty-fourth instance of trouble occurred at 3:00 p.m.
55. The fifty-fifth instance of trouble occurred at 4:00 p.m.
56. The fifty-sixth instance of trouble occurred at 5:00 p.m.
57. The fifty-seventh instance of trouble occurred at 6:00 p.m.
58. The fifty-eighth instance of trouble occurred at 7:00 p.m.
59. The fifty-ninth instance of trouble occurred at 8:00 p.m.
60. The sixtieth instance of trouble occurred at 9:00 p.m.
61. The sixty-first instance of trouble occurred at 10:00 p.m.
62. The sixty-second instance of trouble occurred at 11:00 p.m.
63. The sixty-third instance of trouble occurred at 12:00 a.m.
64. The sixty-fourth instance of trouble occurred at 1:00 a.m.
65. The sixty-fifth instance of trouble occurred at 2:00 a.m.
66. The sixty-sixth instance of trouble occurred at 3:00 a.m.
67. The sixty-seventh instance of trouble occurred at 4:00 a.m.
68. The sixty-eighth instance of trouble occurred at 5:00 a.m.
69. The sixty-ninth instance of trouble occurred at 6:00 a.m.
70. The seventieth instance of trouble occurred at 7:00 a.m.
71. The seventy-first instance of trouble occurred at 8:00 a.m.
72. The seventy-second instance of trouble occurred at 9:00 a.m.
73. The seventy-third instance of trouble occurred at 10:00 a.m.
74. The seventy-fourth instance of trouble occurred at 11:00 a.m.
75. The seventy-fifth instance of trouble occurred at 12:00 p.m.
76. The seventy-sixth instance of trouble occurred at 1:00 p.m.
77. The seventy-seventh instance of trouble occurred at 2:00 p.m.
78. The seventy-eighth instance of trouble occurred at 3:00 p.m.
79. The seventy-ninth instance of trouble occurred at 4:00 p.m.
80. The eightieth instance of trouble occurred at 5:00 p.m.
81. The eighty-first instance of trouble occurred at 6:00 p.m.
82. The eighty-second instance of trouble occurred at 7:00 p.m.
83. The eighty-third instance of trouble occurred at 8:00 p.m.
84. The eighty-fourth instance of trouble occurred at 9:00 p.m.
85. The eighty-fifth instance of trouble occurred at 10:00 p.m.
86. The eighty-sixth instance of trouble occurred at 11:00 p.m.
87. The eighty-seventh instance of trouble occurred at 12:00 a.m.
88. The eighty-eighth instance of trouble occurred at 1:00 a.m.
89. The eighty-ninth instance of trouble occurred at 2:00 a.m.
90. The ninetieth instance of trouble occurred at 3:00 a.m.
91. The ninety-first instance of trouble occurred at 4:00 a.m.
92. The ninety-second instance of trouble occurred at 5:00 a.m.
93. The ninety-third instance of trouble occurred at 6:00 a.m.
94. The ninety-fourth instance of trouble occurred at 7:00 a.m.
95. The ninety-fifth instance of trouble occurred at 8:00 a.m.
96. The ninety-sixth instance of trouble occurred at 9:00 a.m.
97. The ninety-seventh instance of trouble occurred at 10:00 a.m.
98. The ninety-eighth instance of trouble occurred at 11:00 a.m.
99. The ninety-ninth instance of trouble occurred at 12:00 p.m.
100. The hundredth instance of trouble occurred at 1:00 p.m.

Notation and Definitions

$\#_{FM/FB}$	The mean number of FM/FBs generated per unit time.
$\#_{PTR}$	The mean number of PTRs generated per unit time.
$\#_{TOTAL}$	The mean number of TRs generated per unit time.
$\#_{UTR}$	The mean number of UTRs generated per unit time.
β	The mean number of common cause TRs predicted per correct FM/FB.
Θ	The overall mean time that faults are fixed by the maintenance system.
$\theta_{FM/FB}$	The mean inter-arrival time of FM/FB faults.
μ_i	The mean time that worker i takes to fix a fault.
θ_{UTR}	The mean inter-arrival time of unpredictable trouble reports.
a_i	Denotes the arrival of the i th fault.
d_i	Denotes the departure of the i th fault.
n	Number of workers in the model.
PP	Predictive power. The percentage of FM/FB lines that are seen as TRs within 3 weeks of becoming FM/FB.
$QLength$	The current length of the queue. If a fault is arriving it is the current length of the queue without the arriving fault.

Table of Contents

Declaration	i
Acknowledgments	ii
Abstract	iii
Glossary of terms	v
Notation	viii
List of Figures	xii
List of Tables	xvi
1 THE ROLE OF FAULT PREDICTION IN A TELECOMMUNICATIONS MAINTENANCE SYSTEM	1
2 LITERATURE SURVEY	9
2.1 SYSTEM MODELLING AND SIMULATION	10
2.2 FAULT IDENTIFICATION AND CORRELATION	11
2.3 PREDICTIVE MAINTENANCE	12
2.4 NETWORK MANAGEMENT	15
3 TELSTRA'S CURRENT NETWORK MAINTENANCE SYSTEM	17
3.1 A GENERAL DESCRIPTION OF FAULT MANAGEMENT SYSTEMS	18
3.2 THE CUSTOMER ACCESS NETWORK (CAN)	20
3.3 WHAT METHODS OF FAULT DETECTION ARE USED?	22
3.3.1 <i>Customer reported faults</i>	23
3.3.2 <i>Data used to predict future customer TRs</i>	24
3.4 SCHEDULING AND FIXING FAULTS	27
3.5 PREDICTIVE MAINTENANCE AND TELSTRA'S CURRENT SYSTEM	28

4	ANALYSIS OF FAULT MARK (FM) AND FAULT BLOCK (FB) DATA..	29
4.1	THE "PREDICTIVE POWER" OF FM/FB DATA	30
4.1.1	<i>Identifying characteristics to improve predictive power</i>	<i>30</i>
4.2	WHAT PERCENTAGE OF THE DAILY TR VOLUME CAN BE PREDICTED?	34
4.3	ANALYSIS OF THE DELAY BETWEEN THE ARRIVAL OF A FM/FB AND THE ARRIVAL OF THE PREDICTED TR.....	35
4.4	ANALYSIS OF THE CONSISTENCY OF FB LINES	37
4.5	ANALYSIS OF THE RELATIONSHIP BETWEEN THE NUMBER OF TIMES A LINE IS FB AND THE PREDICTIVE POWER.....	38
4.6	SUMMARY OF FM/FB DATA ANALYSIS	41
5	MODELLING TELSTRA'S CAN MAINTENANCE SYSTEM	43
5.1	SYSTEM MODELLING - THE FIRST STEP	44
5.2	CLASSIFYING A MODEL OF TELSTRA'S CAN MAINTENANCE SYSTEM	44
5.3	MODELLING THE FIELD STAFF AND THE FAULT FIXING PROCESS	47
5.4	DEFINING MODEL PARAMETERS	48
5.4.1	<i>Calculating the mean UTR inter-arrival time.....</i>	<i>49</i>
5.5	MODELLING THE RELATIONSHIP BETWEEN FM/FB AND PTR.....	51
5.6	MODELLING THE QUEUE AND FAULT DESPATCH SYSTEM.....	52
5.6.1	<i>Different prioritisation schemes.....</i>	<i>53</i>
5.7	MODEL ASSUMPTIONS.....	58
5.8	PERFORMANCE MEASURES.....	60
5.9	SIMULATING THE MODEL OF TELSTRA'S CAN MAINTENANCE SYSTEM.....	62
5.10	SUMMARY OF MODELLING TELSTRA'S CAN MAINTENANCE SYSTEM.....	67
6	IDENTIFICATION OF OPERATING CONDITIONS THAT IMPROVE SYSTEM PERFORMANCE.....	69
6.1	EXPERIMENT 1: SYSTEM PERFORMANCE WHEN PTRs ARE NOT CLEARED WITH THE FM/FBs THAT PREDICT THEM	70

6.1.1	<i>Reducing TR volume</i>	71
6.1.2	<i>Reducing maintenance workload</i>	73
6.1.3	<i>Reducing mean TR system time</i>	74
6.1.4	<i>The effect of varying β</i>	75
6.1.5	<i>Different maintenance priority schemes</i>	77
6.1.6	<i>Experiment one conclusions</i>	80
6.2	EXPERIMENT 2: SYSTEM PERFORMANCE WHEN PTRs ARE CLEARED WITH THE FM/FBs THAT PREDICT THEM	82
6.2.1	<i>Reducing TR volume</i>	83
6.2.2	<i>Reducing maintenance workload</i>	85
6.2.3	<i>Reducing mean TR system time</i>	88
6.2.4	<i>The effect of varying β</i>	89
6.2.5	<i>Different maintenance priority schemes</i>	90
6.2.6	<i>Experiment two conclusions</i>	93
6.3	EXPERIMENT 3: ANALYSIS OF ESTIMATED TIME TO FIX (ETF) PRIORITY SCHEME	95
6.3.1	<i>Reducing TR volume</i>	96
6.3.2	<i>Reducing maintenance workload</i>	97
6.3.3	<i>Reducing mean TR system time</i>	98
6.3.4	<i>Reduce the number of TRs that have a system time greater than a predefined cut-off</i>	100
6.3.5	<i>Sensitivity of ETF Priority scheme to the system time cut-off</i>	103
6.3.6	<i>Experiment three conclusions</i>	106
7	CONCLUSION	109
7.1	FM/FB DATA ANALYSIS	110
7.2	MODELLING AND SIMULATING TELSTRA'S CAN MAINTENANCE SYSTEM	112
	REFERENCES	115
	APPENDIX A	119
	APPENDIX B	122

List of Figures

Figure 1.1: An example of how a fault at a shared network element may affect multiple customers	3
Figure 1.2: A desired cycle of operation that could be produced by predictive maintenance.....	6
Figure 3.1: Effects of customer and supplier fault detection.....	19
Figure 3.2: A typical representation of Telstra's Customer Access Network.....	20
Figure 3.3: The distribution of the CAN through pillars and joints.	22
Figure 3.4: Processing customer TRs. From reporting a fault to despatching to the field	23
Figure 3.5: The FM/FB testing procedure	26
Figure 4.1: The separation of FM/FB data into groups with specific characteristics...	31
Figure 4.2: The predictive power of different characteristics of FM/FB data.....	32
Figure 4.3: Predictive power of the tickets of work (ToWs) for each group.....	33
Figure 4.4: Percentage of daily TR volume predicted by each group	35
Figure 4.5: The percentage of predicted TRs that arrive each day after they are first predicted by FB data.....	36
Figure 4.6: The percentage of predicted TRs that arrive each day after they are first predicted by FM data.....	37
Figure 4.7: The percentage of FB lines found in each category	39
Figure 4.8: Predictive power of each group.....	39
Figure 5.1: A single server queuing system.....	45
Figure 5.2: State transitions in a fault management system	46
Figure 5.3: System model of Telstra's CAN maintenance system.....	47
Figure 5.4: Different operating regions of equation (5.5)	51

Figure 5.5: PTR generation process.....	52
Figure 5.6: Example of a TR priority queue.....	54
Figure 5.7: Illustrating the cut-off point in every queue.....	55
Figure 5.8: Decision process to prioritise an arriving UTR with an ETF greater than or equal to the cut-off.....	57
Figure 5.9: Example of the prioritisation of UTRs when their ETF is greater than the cut-off.....	58
Figure 5.10: Telstra's CAN maintenance system modelled in Extend™.....	63
Figure 5.11: Composition of the Telstra field worker block.....	64
Figure 5.12: Composition of the Fault Generator block.....	65
Figure 5.13: A comprehensive model of Telstra's CAN maintenance system.....	67
Figure 6.1: Predictive power required to reduce TR volume.....	72
Figure 6.2: Predictive power required to reduce maintenance workload.....	73
Figure 6.3: Predictive power required to reduce mean TR system time.....	74
Figure 6.4: Predictive power required to reduce mean TR system time for different β	76
Figure 6.5: Predictive power required to reduce maintenance workload for each maintenance priority scheme.....	78
Figure 6.6: Predictive power required to reduce mean TR system time for each maintenance priority scheme.....	79
Figure 6.7: The minimum predictive power required to reduce each performance measure when β equals 2.....	81
Figure 6.8: Predictive power required to reduce TR Volume when matching FM/FBs with the PTRs they predict.....	83
Figure 6.9: Predictive power required to reduce TR Volume when matching FM/FBs with the PTRs they predict.....	84
Figure 6.10: Predictive power required to reduce maintenance workload when matching FM/FBs with the PTRs they predict.....	85
Figure 6.11: Predictive power required to reduce maintenance workload for different β when matching FM/FBs with the PTRs they predict.....	87

Figure 6.12: Predictive power required to reduce mean TR system time when matching FM/FBs with the PTRs they predict.....	88
Figure 6.13: Predictive power required to reduce mean TR system time for different β when FM/FBs are matched with the PTRs they predict	89
Figure 6.14: Predictive power required to reduce maintenance workload for each maintenance priority scheme when matching FM/FBs with the PTRs they predict.....	90
Figure 6.15: Predictive power required to reduce mean TR system time for each maintenance priority scheme when FM/FBs are matched with the PTRs they predict.....	91
Figure 6.16: A break down of the TR volume for FM/FB Priority and No Priority schemes.	92
Figure 6.17: A break down of the mean TR system time for the FM/FB Priority and No Priority schemes.	93
Figure 6.18: The minimum predictive power required to reduce maintenance workload and mean TR system time when β equals 2.....	95
Figure 6.19: Predictive power required to reduce TR volume	97
Figure 6.20: Predictive power required to reduce maintenance workload	98
Figure 6.21: Predictive power required to reduce mean TR system time	99
Figure 6.22: A break down of the mean TR system time for the FM/FB Priority, No Priority and ETF Priority schemes.....	100
Figure 6.23: Number of TRs that have a system time greater than 16 hours	101
Figure 6.24: Number of PTRs that have a system time greater than 16 hours	102
Figure 6.25: Number of UTRs that have a system time greater than 16 hours	102
Figure 6.26: Sensitivity of mean TR system time to variations in UTR system time cut-off.....	104
Figure 6.27: The sensitivity of the number of TRs with a system time greater than the cut-off to variations in cut-off time.....	105
Figure 6.28: The reduction in the number of TRs that miss a system time cut-off.....	106
Figure 6.29: The minimum predictive power required to reduce each performance measure when β equals 2	108

Figure A.1: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals two.....	120
Figure A.2: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals three.....	120
Figure A.3: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals four.....	121
Figure B.1: Distribution of delay between FM/FB and customer PTRs.....	123

List of Tables

Table 4.1: Analysis to determine the consistency of FB lines	38
Table 5.1: Model assumptions.....	59
Table 6.1: Parameter values	71

The job of fault prediction in a telecommunications maintenance system

Chapter 1

The role of fault prediction in a telecommunications maintenance system

As we reach the beginning of a new century of technological advances, deregulation of the telecommunications industry and customer expectations are rapidly changing the way that many telecommunications companies do business. Australia's Telstra is one such company investigating ways to improve its position in the market by using advanced technologies to upgrade services to customers. Telstra is Australia's largest telecommunications company. It has a customer base of 6.9 million residential lines and 2.7 million business lines and its network carries around 15 billion calls a year [21]. A key area in which Telstra is significantly able to improve service is network maintenance.

A traditional network maintenance approach, one that is still used by Telstra today, is to rely on customers to detect and report network problems. We call this a *reactive* maintenance scheme as companies 'react' to customer reported problems. It is hypothesised that Telstra's reactive maintenance approach is a legacy from days when it monopolised Australia's telecommunications market and basic network monitoring equipment was very primitive and expensive. The greatest advantage of a reactive maintenance scheme is that only customer affecting faults are attended. This means that resources are not wasted correcting problems that customers will not detect. Another advantage is that network monitoring and testing equipment does not need to be purchased, operated and maintained.

However, relying on customers to detect and report faults is no longer an efficient method of network management. Firstly, technological advances in all aspects of daily life have meant that Australian customers are less tolerant of faults and poor service. Different customers will have different expectations of the telephone service they receive. When some customers detect a problem with their phone they may not be too inconvenienced. If Telstra is able to quickly and effectively repair that problem that customer may be left feeling very satisfied. However, other customers may be immediately dissatisfied with Telstra when they detect a problem with their phone. This dissatisfaction may come from the inconvenience of being without a phone or it may come from an unrealistic expectation that their phone should never be faulty. Having to find a phone to report the fault and having to wait to have their service restored only increases their dissatisfaction. Secondly, relying on customers to detect and report faults can lead to higher maintenance costs as maintenance can not be planned. By operating a

reactive maintenance system telecommunications companies are rarely able to identify faults that are related by a common cause. Often a number of faults will result from a single common fault as can be seen in Figure 1.1.

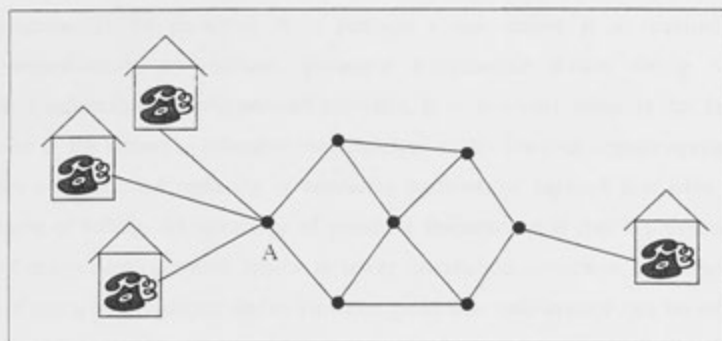


Figure 1.1: An example of how a fault at a shared network element may affect multiple customers.

If there is a fault at node 'A' then the three customers on the left of Figure 1.1 will all experience problems. When they detect these problems they will each individually call their telecommunications provider to report a fault with their service. By having a reactive maintenance scheme, the company only becomes aware of faults when each customer reports them. These customer reports may not be made at the same time; they may be made over the course of several days. Therefore when the company receives the first call it will send a worker to fix that fault. It will then receive a second call and another worker will be sent to fix that fault, and similarly with the third fault. This example demonstrates how costly a reactive maintenance scheme can be as three workers are sent to fix a fault that could have been fixed by a single worker.

If the telecommunications company itself were able to detect network faults it may have been able to correlate the three faults as a single fault at the common node. As a result only one worker would be sent to fix the common fault resulting in a large saving in time and money. If the company were able to quickly repair the common cause fault then the three customers may never realise that there was a problem and so have no cause to question service quality. Even if a customer did detect a problem then the company could tell them that it was aware of that problem and that measures had

already been taken to rectify it. This would increase customer confidence, and also reduce waiting time for service restoration.

A common method that tries to prevent network faults from occurring is *proactive maintenance*. To be proactive is to perform a task before it is required. In a telecommunications environment, proactive maintenance means fixing network problems before they become network problems. In other words, ensuring that faults do not arise in the network. Proactive maintenance usually involves regular servicing of network elements and replacing or upgrading parts of the network that have a high likelihood of failing. An advantage of proactive maintenance is that it prevents many faults from occurring, which results in fewer dissatisfied customers and reduces the costs of reactively repairing faults. However proactive maintenance can be relatively costly as network elements are replaced or serviced when they are not faulty. Another problem is that tampering with a telecommunications network often increases the likelihood of a fault occurring. This is because telecommunications networks are a complex web of electrical components and while servicing one part of the network a worker may inadvertently affect another part. Also when a customer affecting fault does occur in the network proactive maintenance does not prevent that customer from reporting the fault.

An alternative maintenance approach, one that is the basis for this thesis, is *predictive maintenance*. In a telecommunications environment a predictive maintenance scheme monitors a network and identifies problems. It then predicts which of these problems customers will report in the future. One advantage of predictive maintenance is that there is time to fix faults that you predict customers will report before customers detect and report them. These customers will never realise there was a problem and would have no cause to be dissatisfied with the service provided. Another advantage is that maintenance can be planned so that common cause faults are identified. This could greatly reduce the maintenance workload as a worker fixing a single fault would fix many potential customer trouble reports (TRs). A disadvantage of predictive maintenance is when future TRs are incorrectly predicted. These incorrect predictions, which are called false alarms, can result in an increase in work as field staff fix faults that would not be reported by customers. These faults would not be fixed in a reactive maintenance scheme. False alarms also impact on customers as fixing false alarms

occupies resources that could be used to fix genuine faults reported by customers, thus increasing customer waiting time. Predictive maintenance should not be confused with proactive maintenance. Predictive maintenance does not prevent faults from occurring. It simply predicts which faults customers will report and attempts to correct these faults before customers detect the problem.

In this thesis the performance of three predictive maintenance schemes is compared against the performance of a reactive maintenance scheme. These three schemes use prioritisation rules so that different fault types are prioritised under different conditions. The performance of each scheme is measured by three performance measures: 1) the *TR volume*, which is the number of customer TRs received over a period of time; 2) the *maintenance workload*, which is the number of faults that the field staff must fix; and 3) the *mean TR system time*, which is the average time a customer TR must wait between being reported and being fixed.

If all three performance measures can be reduced, a continuous cycle of operation may be achieved. A reduction in TR volume may reduce the maintenance workload; this depends on the percentage of false alarms and the number of common cause faults. If this occurs then a reduction in TR volume and maintenance workload may also lead to a reduced TR system time. When all three performance measures are reduced field workers have more time for predictive maintenance and the cycle starts again. This cycle of operation is a desired outcome from a predictive maintenance scheme and it is illustrated in Figure 1.2.

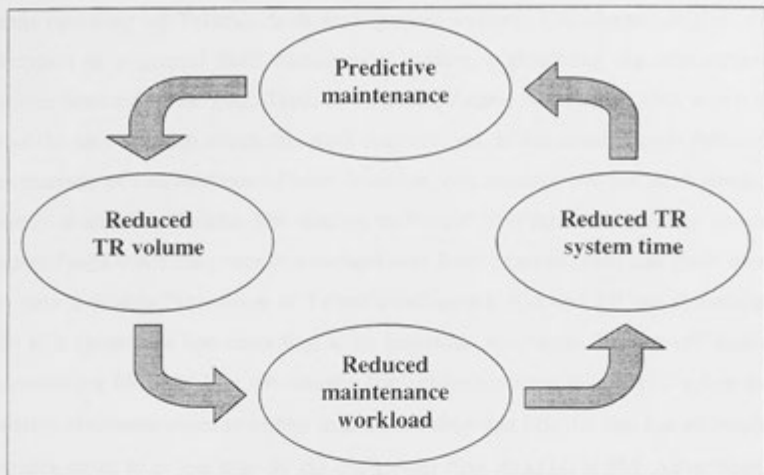


Figure 1.2: A desired cycle of operation that could be produced by predictive maintenance.

The primary goal of this thesis is to identify operating conditions under which the cycle shown in Figure 1.2 can be achieved. This is done using computer simulation to estimate the performance of each maintenance prioritisation scheme under different operating conditions. By operating in this cycle telecommunications companies will be able to significantly reduce their maintenance costs and their number of dissatisfied customers. In today's highly competitive telecommunications market, both of these characteristics are highly sought after.

The first step toward achieving the stated goal is to develop an understanding of relevant work done by other people. The work performed in this thesis can be classified into four areas: system modelling and simulation, fault identification and correlation, predictive maintenance and network management. Chapter two provides a literature survey of work that has been done in each of these areas. In the literature survey we look at the contributions of various authors and discuss the relevance of their work to the work presented in this thesis.

Before we are able to model and simulate Telstra's fault management system we must first develop an understanding of its current operation. Chapter three examines the

current operation of Telstra's fault management system. The chapter begins with a description of a general fault management system, highlighting the implications of customer detected faults. Then Telstra's Customer Access Network (CAN), which is the part of the network with which this work is concerned, is described. This is followed by a comparison of two methods of fault detection, one reactive and the other predictive, currently available to Telstra. The reactive method of fault detection relies on customers to report faults while the predictive method uses Fault Marked (FM) and Fault Blocked (FB) data available from some of Telstra's exchanges. FM and FB are classifications given to a customer's line according to its insulation resistance. The cut-off insulation resistances for FMs and FBs are variable but Telstra's current rules are: if a line has an insulation resistance equal to or less than $20\text{ k}\Omega$ then it is FB; if a line has an insulation resistance equal to or less than $50\text{ k}\Omega$ but greater than $20\text{ k}\Omega$ it is FM. Advantages and disadvantages of each method are discussed. Finally, an explanation of the process that is used to assign field workers to fix the faults and how the faults are cleared from Telstra's records is given.

Before Telstra can implement a predictive maintenance scheme using FM/FB data it must first understand the dynamics and limitations of this data. Chapter four analyses historical FM/FB and TR data to develop an understanding of how FM/FB data may best be used in a predictive maintenance scheme. An essential element of predictive maintenance is knowing the accuracy of the TR predictions. We call the percentage of FM/FBs that accurately predict future TRs the *predictive power*. By analysing historic FM/FB and TR data we calculate the predictive power of FB lines and FM lines to be 11.8% and 7.7% respectively. To increase these values we analyse FM/FB lines to identify the characteristics of lines that are most likely to predict future customer TRs. We also determine what percentage of the daily TR volume can be predicted, and possibly prevented, by a predictive maintenance scheme using FM/FB data. The time between when a line is first FM/FB and when it is reported by customers is critical as it is the time that Telstra have to fix FM/FB lines if it wants to prevent future customer TRs. This delay time is examined and distributions of the delay are separately calculated for FM and FB lines. In an attempt to explain the low predictive power of FB lines we examine the consistency of FB lines to determine if they are mostly intermittent faults that randomly appear and disappear. Finally we evaluate the relationship between the

number of times a line is FB and its predictive power and we discuss why this result can not be practically used by Telstra.

To achieve the cycle of operation shown in Figure 1.2 we must model Telstra's CAN maintenance system and define the maintenance priority schemes that we will use. Both of these are achieved in chapter five. We model Telstra's CAN maintenance system as a stochastic discrete event queuing network. A system model of Telstra's CAN maintenance system is presented and the implications of modelling the system in this way are discussed. The system model that we have created demonstrates a relationship between FM/FB and TR data that has not been understood before now. This relationship takes into account predictive power, mean number of common cause faults and the delay between the arrival of a FM/FB and the arrival of the TR(s) it predicts. The performance measures that are used in the simulation analysis are presented along with the maintenance priority schemes. Finally we discuss why simulation is used to evaluate the performance of our model and how this is achieved.

In chapter six we present the simulation analysis, which is divided into three separate experiments. The first experiment does not clear predicted TRs from the queue when the FM/FB that predicts them is fixed. This is analogous to Telstra not being able to identify which TRs have been predicted by which FM/FBs. This was done to initially keep the simulation simple so that the results may be interpreted and understood. In this experiment we determine the maintenance priority scheme, predictive power and mean number of common cause faults that reduce the TR volume, the maintenance workload and the mean TR system time with the lowest predictive power. The second experiment does match FM/FBs with the TRs they predict. The results from this analysis are compared with the results from experiment one and the implications of clearing predicted TRs with the FM/FBs that predict them are highlighted. The final experiment analyses the performance of an Estimated Time to Fix (ETF) Priority scheme. This experiment is designed to minimise the number of times Telstra do not meet a Customer Service Guarantee (CSG), as well as to help reduce the mean TR system time. Again we determine the maintenance priority scheme that reduces the TR volume, the maintenance workload and the mean TR system time with the lowest predictive power. We also investigate the sensitivity of results to variations in the system time cut-off.

Chapter 2

Literature Survey

The areas of study in this project can be divided into four key areas: system modelling and simulation, fault identification and correlation, predictive maintenance, and network management. The following literature survey presents the contributions of various authors to these areas and discusses the relevance of this thesis in light of their work.

2.1 System modelling and simulation

System modelling is a valuable engineering tool that has been used to help understand and solve real world problems for many years. Waller, Triscari and Owens [23] explain how modelling can be utilised in large engineering projects. The authors demonstrate a use for modelling in the various stages of a project life-cycle such as risk reduction, design, technical performance measurement, verification and validation, test, evaluation and acceptance, technical transfer and research and development. In terms of our project, our model is used in the risk reduction process, the design process, and the research and development process.

In discrete event system (DES) modelling there are two common methods for determining system performance: analytical equations and computer simulation. Analytical models are discussed by both Cassandras [4] and Buzacott and Shanthikumar [3]. Cassandras looks at modelling DES using both Markov chain theory and general queuing theory while Buzacott and Shanthikumar use queuing theory to analyse specific manufacturing systems. Cassandras explains the importance and applications of DES in more detail than Buzacott and Shanthikumar who primarily solve many different stochastic manufacturing models. In our project we do not use analytical models as they are restrictive in the types of systems and problems they can solve. We can not define a set of analytical equations that accurately describe our system's behaviour as our analysis requires us to monitor and make decisions upon specific random events. For example when a FM/FB fault is fixed we need to know which TRs have a common cause so that they can be fixed along with the FM/FB. Therefore, we use computer simulation to evaluate the performance of our model. Cassandras introduces the reader to DES simulation and discusses simulation of queuing systems. Cassandras and Brately, Fox and Schrage [2] discuss the analysis of simulation outputs, specifically for finite-horizon simulation, which we have used.

2.2 Fault identification and correlation

Communications networks are very complex systems composed of thousands of interconnected nodes from various manufacturers. Therefore when network failures occur it is possible that a very large number of alarm messages are generated. These alarms can be used to establish the location and cause of the fault but at the same time the high volume can make this extremely difficult. As a result fault identification and correlation based on network alarms has become a high priority for many telecommunications companies.

Fault identification consists of three phases: fault detection, fault localisation and fault testing. Bouloutas, Calo and Finkel [1] and Katzela and Schwartz [10] are primarily concerned with fault localisation. Both present a dependency graph based approach that utilises algorithms to solve the alarm correlation and fault identification problem. Meira and Nogueira [12] propose a general model for a telecommunication network so that they can study network management applications, specifically in the development of models for alarm correlation.

Another approach to fault correlation is to utilise artificial intelligence (AI) techniques. AI techniques such as neural networks can be effectively used in the alarm correlation domain. They are adaptive systems with a parallel architecture that can learn and generalise from input data. One advantage is that neural networks can often recognise patterns even when the input data is noisy, corrupted or has a lot of variation. The disadvantage is that they require intensive training before being able to associate an output pattern with a given input pattern. This is not always convenient in a telecommunications environment where all the alarm signatures of fault occurrences may not be known. The work performed by Wu, Bhatnagar, Epshtein, Bhandaru and Shi [24] describes a system called the alarm correlation engine (ACE) that is used by GTE in its US local exchange networks. ACE aids network management by correlating alarms on the basis of common cause. It also has the capability to carry out prescribed responses, which greatly improves response time and increases productivity. ACE uses a domain specific correlation language that GTE believe makes it very efficient as well as flexible. Gardner and Harle [5] also use a purpose designed language to specify alarm patterns and then use the results in a real-time correlation engine. Gardner and Harle specify the correlation framework they used as well as give a thorough description of

the correlation language and how it is constructed. All of the fault identification and correlation approaches mentioned so far differ from our study of alarm correlation as we only receive fault alarms (FM/FB data) from a single point in the network (Telstra's Ericsson supplied AXE exchanges). We also do not receive different fault alarms according to different types of faults. We only obtain alarms (FM/FB) based on a line's insulation resistance. Our fault correlation is more like that used by Telstra in the early 1990's with its pressurised cable alarm monitoring system. Kashmirian and Robinson [9] describe Telstra's automatic pressurised cable monitoring system (APCAMS) which monitors the pressurised cables in Telstra's network. The major types of alarms generated by APCAMS are for low pressure, noisy transmission, no response, high pressure and any pressure changes outside of 10 kPa. Due to the dynamic nature of the network, cable pressures are constantly varying and as a result there is a continuous stream of information and alarms. The network operators were receiving too much information and as a result many poor operating decisions were being made. This led to the development of the alarm evaluation system that filters the alarms that are forwarded onto the network operators. The filtering of alarms in this case is very rule based, ie certain alarm types are only transmitted if there are more than three such alarms on the same cable pair within a specified short period of time. This type of correlation is similar to the way in which we are correlating our faults. For example when we are looking for common cause faults we only count FM/FB alarms if there are two or more FM/FB lines closely situated in the network.

2.3 Predictive maintenance

The ability to predict future events has long been a desirable talent. From tea leaves to tarot cards, it was always believed that predicting future events required either luck or psychic powers. However, technological advances mean that this situation may be rapidly changing. Grayson [7] writes that Computer Associates are developing software that uses neural network technology to predict the future. Called Neugents, the technology makes its predictions by analysing vast amounts of data. Based on historical information and present conditions, it makes predictions about what will happen in a given situation in the future. One of the earliest applications for Neugents has been to predict when a server or other device on a network is going to fail. Armed with such knowledge network administrators can take preventative steps before the failure occurs. This is a form of proactive maintenance that, as was mentioned in chapter 1, is different

to predictive maintenance. Predictive maintenance doesn't try to predict when devices are going to fail. Predictive maintenance is only concerned with predicting faults that customers will report.

Telstra has trialed predictive maintenance schemes in the past as described by McIntyre [11]. This scheme was the customer access network evaluation system (CANES) that was used by Telstra in the early 1990's for predictive maintenance. McIntyre states that studies have shown that services that have an insulation resistance between 50 k Ω and 500 k Ω are very likely to incur "service affecting" faults within twelve months. CANES utilised an expert system that applied a set of rules to line insulation quality data, network configuration data, fault history and customer fault reports. The recommendations of the expert system were used for long term management of network upgrade programs and to assist despatch of fault repair staff. The CANES analysis was based on a combination of connectionist and rule based reasoning that was driven by the actual network configuration. This resulted in a robust system that could diagnose and assist in the location of faults even when the knowledge base was incomplete. The CANES system was never fully implemented as the network configuration database was never completed. Both our project and CANES use line insulation quality to predict future customer reports. However our project utilises FM/FB data obtained from AXE switches while CANES used customer line insulation quality (CLIQ) tests. CLIQ tests are prohibitive in the number of lines that can be tested as they are usually only performed at night due to the occupation of a customer line for the test. Also CANES is more of a proactive maintenance scheme, detecting trouble lines that are degrading and that may be problems within the next 12 months. Our project has a much shorter time frame than that, mostly trying to predict customer TRs that will arrive in the next 3 weeks.

Other telecommunications companies such as British Telecom (BT) and GTE have also implemented predictive maintenance schemes. Potts [17] describes British Telecom's (BT's) access network support system (ANSS). Previous BT support systems were designed to support a purely copper based network. The main aim of ANSS is to enhance and supplement these systems to support similar processes using fibre and radio, as well as enhanced copper technology. New technology, which has the in built capability to monitor its own ability to support service correctly, will mean that network

status reports are produced automatically. In order to reduce the number of customer reported faults, ANSS will automatically take appropriate action upon receiving fault alarms from network elements. ANSS will also analyse all the fault alarms they receive with the aim of correlating alarms and identifying a single point of failure in the network. Silver, Qian, Moghe, Eichen, Doleac, Bhatnagar and Friedman [20] discuss TCAF, an expert system that performs 24-hour monitoring and surveillance of the customer access facilities in GTE's telephone network. The aim of the system is to identify and fix developing faults before a customer detects a problem. The key idea is to use alarms from a digital switch to trigger testing. This allows the test to be performed near the time of a failure (and hence more likely to detect intermittent faults) and also focuses the testing effort in areas of likely trouble. Results have shown that TCAF has reduced the number of customer reported faults by approximately 85%. TCAF has also been approximately 90% accurate in detecting faults that can not be predicted such as cable cuts. Early detection of unpredictable faults allows GTE to get repair crews in place quickly, before a large number of customers become aware of the problem. The work at both BT and GTE is similar to our project as we are both attempting to reduce the number of customer reports received by fixing faults before a customer detects them. They also try to identify common cause faults. However, neither of the systems mention the effects of fixing future TR predictions that do not result in a customer reported fault. In these instances workers and resources are used while customers wait to have their faults repaired. Our project investigates the effect of fixing false alarms and we establish operating conditions that ensure more effective utilisation of the field staff.

Schmersal [19] and Pierce [16] both recognise the importance of predictive maintenance to improve a customer's perception of network reliability. Schmersal discusses its importance when describing the role of a performance monitoring system. Pierce describes how predictive maintenance is only a small part of an overall approach he calls total service assurance. He states that implementation of total service assurance is vital for a telecommunications company to differentiate itself in the market place. Assurance is the process for maintaining and improving the ongoing quality of service (QoS). It requires a full implementation of four processes: service quality management and customer QoS management, which are proactive in nature; and problem handling and service problem resolution, which are traditional and reactive assurance processes.

Service quality management uses the information provided by modern intelligent network elements (INEs) to detect trouble early. Our project is primarily concerned with what Pierce calls service quality management. The INEs in our network are AXE exchanges that provide FM/FB data.

2.4 Network management

To attain high levels of customer satisfaction and to assist with network maintenance, many companies are searching for ways in which to improve the management of their networks.

In the mid 1990's BT undertook numerous activities aimed at improving the performance of its telecommunications network. However, in order to improve network performance it is important to be able to measure how well it is currently working. Rogers and Hand [18] discuss how BT has changed the way in which it measures network performance. Traditionally BT has used test calls to evaluate the state of its network. Test calls were performed by a system that was able to initiate and answer calls automatically. If any problems were observed during the call set up and call shut down then these were recorded. Approximately 2 million test calls were made a month and from these performance reported, black spots identified and remedial action taken.

Despite the success of these test calls, BT decided to replace them with live call sampling. The strength of live call sampling is that it measures calls going anywhere, needs no far-end answering equipment, and measures continuously 24 hours a day, every day. Most modern exchange systems have a live-call sampling facility as part of their management statistics package. All calls originating, terminating or passing through digital exchanges are eligible to be sampled. This approach to network measurement is analogous to the way we are attempting to use FM/FB data for predictive maintenance purposes. The old method of running batches of CLIQ tests to obtain insulation quality data can be compared to BT's test calls. While using AXE exchanges to test lines can be compared to BT's live-call sampling.

Guido, Roberto, Di Tria and Bisio [8] describe how Telecom Italia has developed workforce management techniques and environments to improve the level of service that it provides customers. The authors discuss many issues such as the analysis of

network maintenance and operations, the evaluation of new processes, the improvements gained through automatic fault dispatch and mobile technicians. Relevant to our work is their use of simulation to analyse the present mode of operation and to help evaluate and develop future modes of operation. This is what we are aiming to achieve with our simulation. We have a benchmark level, which is the present mode of operation, and through simulation we are investigating new operating modes that may perform better than the present mode. Another relevant activity that the authors discuss, and is also discussed by Montana, Bidwell and Moore [13], is resource allocation. The resource allocation algorithm used by Telecom Italia takes into account several different factors such as organisational, legal, technical, human behaviour and contractual constraints. They also have several metrics that need to be optimised including: (i) Activities waiting time: the queue time for the activities. (ii) Correct repair percentage: the percentage of correct trouble repair. (iii) Intervention time: the total time taken to complete each activity. (iv) Medium repair time: the intervention time minus the time spent for travelling, getting equipment etc. (v) Medium trouble time: the time from when the trouble arose to when the trouble was repaired. Montana, Bidwell and Moore discuss the work that has been done by GTE to use genetic algorithms (GAs) for real time scheduling. Real time scheduling can be very difficult due to large search spaces, dynamically changing problems and a variety of constraints. Genetic algorithms are suitable to solve these problems as they can search large, multimodal spaces effectively to find nearly global optima. GAs are also flexible as to the optimisation problems they can solve and have been shown empirically to scale well with problem size. The implementation of a field service scheduler for one of the largest field service organisations in the world has shown resource efficiency improvements of 60 to 100% when measured as the number of service calls closed per day by each service representative. Our resource allocation is comparably simple as we only consider different prioritisation schemes according to the type of fault. We do not try to match jobs with field workers by taking into account any constraints on the field workers such as skills and distance from the next job etc. We assume that all field workers are equally able to repair each fault. The advantage of our approach is that it is relatively simple to model and simulate, yet is still very effective. As soon as you try to match workers with jobs, a complete search of all possible matches becomes computationally unfeasible and more advanced search techniques such as those used by Montana, Bidwell and Moore are required.

Chapter 3

Telstra's current network maintenance system

Before we can begin to investigate how predictive maintenance can be used in Telstra's maintenance system we must first understand its current operation. The aim of this chapter is to familiarise the reader with Telstra's fault management system. Specifically we look at how faults arrive in Telstra's system, how these faults are accepted and tested and then how they are despatched to field staff to be repaired. The chapter concludes with an explanation of the network data that Telstra hope to use for predictive maintenance.

3.1 A general description of fault management systems

Fault management systems are found in any organisation or industry that supplies a product or service to a customer. Typically there is a supplier and a customer as well as a medium across which the product or service is supplied. If the product or service cannot be supplied according to a specified level of performance, or to the customers expectation, then a fault exists that needs to be rectified.

Fault detection can come from either the customer or the supplier. When a customer detects a fault the supplier must provide resources to enable that customer to report the fault. The supplier must then quickly find and rectify the fault in order to minimise that customer's dissatisfaction with the supplier. The provision of customer fault reporting facilities can be very costly to the supplier, not to mention the costs a dissatisfied customer may bring. However, if the supplier can detect and correct faults before a customer realises the problem they do not have to provide customer fault reporting facilities. Also the management of faults becomes less expensive and customers are not dissatisfied. This can be seen graphically in Figure 3.1.

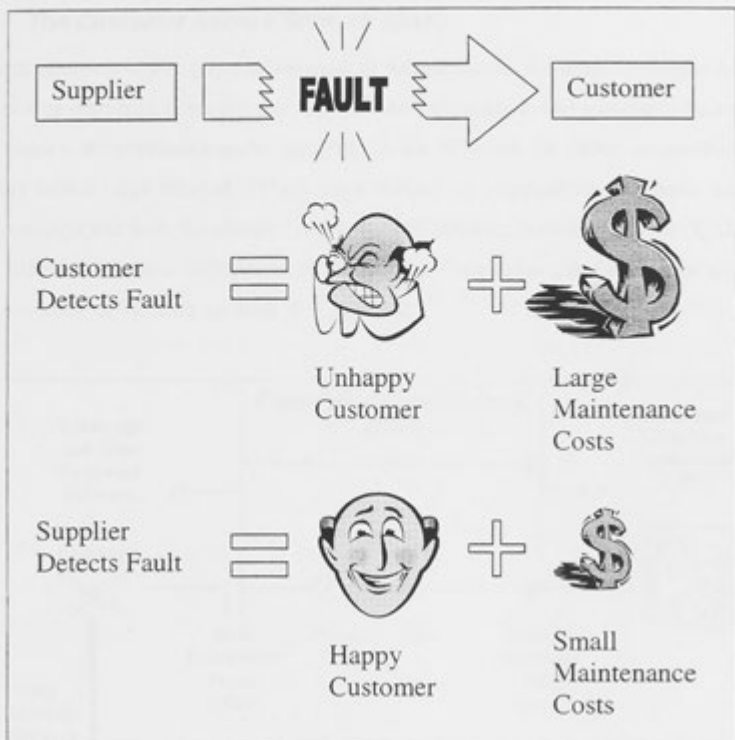


Figure 3.1: Effects of customer and supplier fault detection.

Once detected, a supplier must arrange to fix the fault. All fault management systems will have some form of despatch system that assigns resources to fix faults. Often these resources are trained personnel with specialised fault fixing equipment. Allocation of faults to workers may be based on different criteria such as the skills of workers available, the location of a fault and the time available to fix a fault. Rules for despatching faults will vary for different companies, industries and situations.

Telstra provides many products and services to its customers. However, this work is only concerned with the supply of a telephone service that performs to the expectations of customers.

3.2 The Customer Access Network (CAN)

The maintenance of any physical network in Australia will encounter problems because of the large distances it must cover and the harsh climates it will inevitably be exposed to. Telstra's telecommunications network is no different. In order to maintain and support such a large network Telstra have divided its components into three sections: the Exchange and Inter Exchange Network, the Customer Access Network (CAN) and the Customer Premises Equipment (CPE). These three areas can be seen in a typical representation of Telstra's network in Figure 3.2.

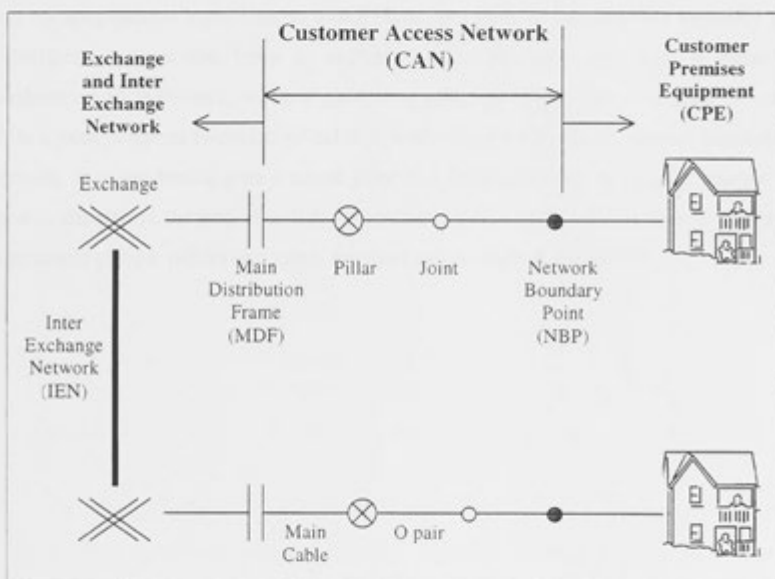


Figure 3.2: A typical representation of Telstra's Customer Access Network.

These three distinctions are made as the technologies and processes used in each area are vastly different. The Exchange and Inter Exchange Network is maintained by Telstra's Network and Technology Group (NTG). The CAN is defined as all the network from the Main Distribution Frame (MDF) at an exchange up to the Network Boundary Point (NBP) at a customer's premises. The part of the network to the right of the NBP is called the Customer Premises Equipment (CPE). The NBP is usually the first telephone socket in a customer's premises. Therefore the CPE is usually the

telephone, modem or fax that a customer has connected. While some CPE may be rented from Telstra, it is not the responsibility of Telstra to maintain this equipment.

This study is only concerned with faults that are located in the CAN. The CAN is the responsibility of Telstra's Commercial and Consumer (C&C) Service business group. A typical representation of Telstra's CAN can be seen in Figure 3.2. It should be noted that the components used between an exchange and CPE will vary from customer to customer and not all components are shown in Figure 3.2. Some customers may be connected directly to the exchange requiring no pillars or joints while others may have other components such as cabinets along their line. Pillars and joints are typically used to distribute the network from an exchange to a customer's premises. A pillar can distribute up to 900 lines, while a joint is a connection between two parts of cable. While a joint connects two parts of cable it is also used to distribute lines to a customer's premises. In a residential area a single joint can distribute lines to up to 8 houses. If a house is situated at the end of a distribution line its line may pass through many joints. An example of how pillars and joints are used can be seen in Figure 3.3

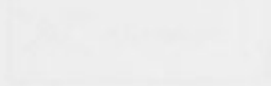


Figure 3.2: Typical representation of Telstra's CAN

3.2.1. Typical representation of Telstra's CAN

The diagram shows a central box labeled 'Exchange' with several lines radiating outwards to other boxes, representing a typical representation of Telstra's CAN. The lines represent distribution lines, and the boxes represent customer premises or other network components. The diagram illustrates how pillars and joints are used to distribute the network from an exchange to a customer's premises.

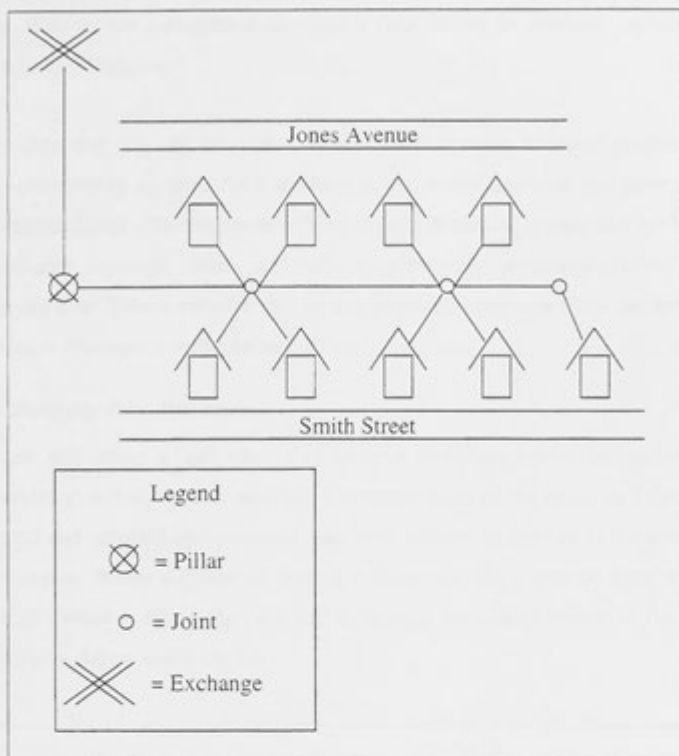


Figure 3.3: The distribution of the CAN through pillars and joints.

3.3 What methods of fault detection are used?

It can be difficult for telecommunications companies to detect network faults as it is hard to clearly define what constitutes a fault. Telecommunications companies can only detect faults by measuring physical characteristics of a customer's line. If that line does not have adequate measurements then there may be a fault with that line. However, it may be the case that the line is still operating, for whatever reason, and the customer is perfectly happy. Sending field staff to correct this fault is a waste of valuable resources. There may be another customer that also has a phone line that has poor electrical measurements. However this customer's phone may be noisy and not very clear. As the phone may still be working the customer will not report the problem as they believe it will go away. In this case a customer's telephone line is not performing to their expectations and as a result they are dissatisfied with their telecommunications

provider. Waiting for a customer to report a fault is not an adequate means of fault detection in this situation.

It can be seen that it is not acceptable to wait for customers to report problems and it may be unnecessary to send field workers to fix every line that has poor electrical measurements. Ideally Telstra needs a flexible fault detection system that is able to use both customer reported faults as well as physically measured faults. We are investigating how Telstra may be able to use physically measured line performance to predict future customer trouble reports (TRs).

3.3.1 Customer reported faults

A customer will report a fault when they become so unhappy with the quality of their phone service that they have to report it. Currently, most of the faults in Telstra's CAN are detected and reported by customers who have noticed a decrease in the performance of their service. When a customer detects a fault with their service they will call a Telstra Call Center to report the fault and to arrange for a field worker to fix the fault. This process is shown in Figure 3.4.

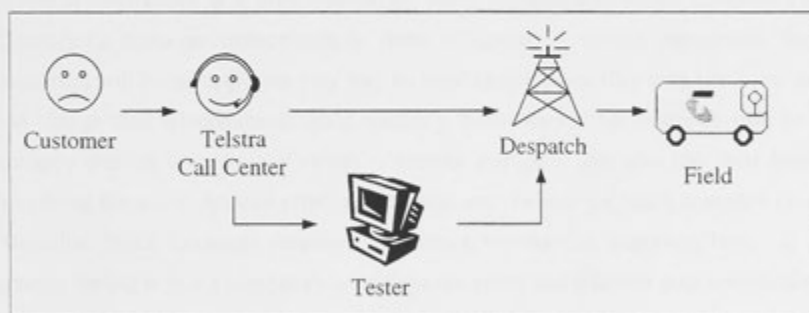


Figure 3.4: Processing customer TRs. From reporting a fault to despatching to the field.

Telstra has consultants in its Call Centers who answer incoming customer TRs. The consultants are trained to ask customers specific questions to determine the type of problems they are experiencing. Some problems, such as no dial tone on a customer's phone, can be tested and identified by the consultant. While other types of customer problems need to be sent to a tester who can conduct more rigorous tests on the line.

Once the fault type has been identified the details are entered into Service Plus which is a management database that is used by Telstra. Service Plus sends the fault to Telstra's despatch system, which allocates it to the next available field worker.

There are both advantages and disadvantages of relying on customers to report network faults. The advantage of using customers to detect faults is that maintenance is performed only when it is necessary. Resources are not wasted fixing problems that are not customer affecting. A disadvantage is that the ability to plan network maintenance is lost. Telstra is forced to react quickly to customer reported faults as it is under a legal obligation to fix faults within time frames that are set out in Telstra's Customer Service Guarantee (CSG) [22]. Having to react so quickly means that Telstra often miss opportunities to identify groups of faults that have a common cause. When this occurs Telstra sends many field workers to fix a number of faults that could be fixed by a single worker. Sending a field worker to fix a fault is very expensive. Therefore Telstra wants to minimise the number of times it sends workers to fix faults. Another disadvantage is the cost of customer dissatisfaction. Deregulation of the telecommunications industry has led to an increase in competition, which means that customer satisfaction is a high priority for every telecommunications company [16]. Quantifying customer unhappiness in terms of dollars is almost impossible. Some customers will be unhappy, but they may be loyal customers or they may not know they can change their telecommunications company. However another customer may be so unhappy that not only do they switch to another company, they also talk their friends into doing the same. Another effect may be that now Telstra is a listed company on the Australian Stock Exchange consumer confidence becomes an important factor. If the general feeling is that a company's operations are smart and efficient then confidence is high and share prices usually rise. However, if confidence in a company is low then people will not want to invest their money in this company and its share prices may fall.

3.3.2 Data used to predict future customer TRs

Fault data can be used to predict future customer TRs. The data Telstra is investigating to use for TR predictions is called Fault Marked (FM) and Fault Blocked (FB) data. This data comes from physically measuring the insulation resistance of a customer line. It is obtained from Telstra's Ericsson supplied AXE exchanges, which currently make

up approximately 65% of Telstra's network. The other 35% consist of Alcatel supplied System 12 exchanges which do not have FM/FB reporting capabilities.

Telstra's AXE exchanges perform regular insulation resistance tests on lines that they connect. A line is tested every time a customer hangs up after receiving a call or after three days if a customer has not received a call in that time. If a line is found to have an insulation resistance of 20 k Ω or less then it becomes FB. A FB line is disconnected from the network by an exchange and its details are stored in a memory buffer in the exchange. FB lines are disconnected as the low resistance causes the exchange processors to go into a loop of sending the line dial tone, then removing the dial tone. This renders the line unusable by a customer. Once FB a line is re-tested every 10 minutes. If the insulation resistance changes so that it is greater than 20 k Ω the line is reconnected and its details are removed from the storage buffer.

A line becomes FM if it has an insulation resistance equal to or less than 50 k Ω but greater than 20 k Ω . FM lines are not disconnected, they are still operable and the user may or may not notice a difference in the quality of their service. Details of FM lines are stored in the same buffer as FB lines. FM lines are re-tested every three hours after becoming FM. If the insulation resistance changes so that it is greater than 50 k Ω the line details are removed from the storage buffer.

The automatic testing capability of AXE exchanges is ideal for a predictive maintenance scheme. However, two questions that relate to it are: 1) Is it testing the most useful measure (insulation resistance)? and 2) Is it testing customer lines that are actively being used? At this stage it is not clear if insulation resistance alone is a line characteristic that greatly influences customer TRs. As FM lines are still operating, does an insulation resistance reading between 20 k Ω and 50 k Ω reduce line performance to a point that is noticeable to a customer? This is a question that requires further investigation. As FB lines are disconnected, FB data can definitely identify lines that customers will detect a problem with if they try to use that line. However, if a customer does not try to use that line they will never detect and report the problem. Therefore, for predictive maintenance the FM/FB testing procedure needs to be modified to ensure only lines that are actively being used by customers are tested.

The testing process that an AXE exchange follows is given in Figure 3.5. It should be noted there is no end to the process as it continues indefinitely.

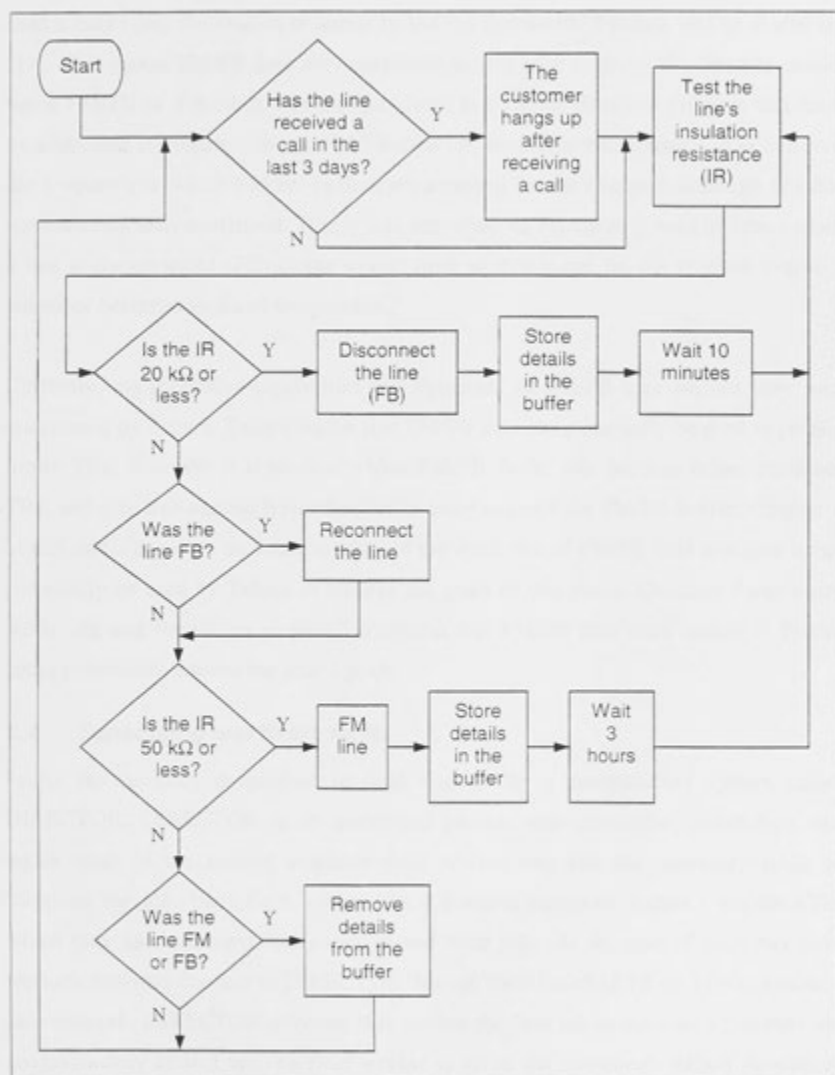


Figure 3.5: The FM/FB testing procedure.

Details of FM/FB lines in the storage buffer are electronically accessed 3 times per day (approximately morning, noon and night) and the contents of the buffer at that time are

downloaded and stored in Telstra's Testing and Diagnosis Server (TADS) database. Andrew Wild of Telstra's NTG stated that "accessing the FM/FB buffers of all of AXE exchanges takes approximately half an hour. If an exchange is under a heavy switching load it may reject the request to access its buffers and no FM/FB data will be available" [14]. This makes FM/FB data very unreliable as it is hard to know if a line has ceased being FM/FB or if no data was accessed from that switch. This is a problem that must be addressed if Telstra is to use FM/FB data for predictive maintenance. It is believed the frequency at which FM/FB buffers are accessed can be changed, although this has not been officially confirmed. This is also important as Telstra may need to detect when a line is disconnected (FB) closer to real time so that it can fix the problem before a customer becomes aware of the problem.

Currently, the predictive capabilities and dynamics of FM/FB data are not very well understood by Telstra. Telstra realise that FM/FB data can potentially be used to predict future TRs. However it is unclear which FM/FB faults will become future customer TRs, and it is also unclear how often faults enter and exit the FM/FB buffer. Chapter 4 of this thesis develops an understanding of the dynamics of FM/FB data and how it can potentially be used by Telstra to achieve the goals of this thesis. Chapters 5 and 6 use modelling and simulation to establish criteria that FM/FB data must satisfy if Telstra could potentially achieve the stated goals.

3.4 Scheduling and fixing faults

Faults are currently despatched to field workers by a computerised system called DIRECTOR. DIRECTOR is an automated process that despatches installation and repair work to the nearest available field worker that has the necessary skills to complete the job. Each field worker has a portable computer called a FieldMATE, which they use to electronically receive and clear jobs. At the start of each day field workers remotely connect to DIRECTOR through their FieldMATE on Telstra's mobile data network. DIRECTOR allocates that worker the first job in the queue that they are geographically closest to. The field worker is given the customer's details as well as what the testers believe to be the fault type. The field worker then has to find the customer's premises, test the line and isolate the fault. Once they have fixed the fault they notify the customer, explaining what they have done. They also clear the fault from DIRECTOR by entering the correct clear code in their FieldMATE. The clear code

describes the type of fault found as well as the actions taken to repair it. DIRECTOR will then assign the field worker a new job.

DIRECTOR is an important part of Telstra's current fault management system as it decides which faults are assigned to which field workers. In a predictive maintenance scheme DIRECTOR would be required to prioritise faults so that certain faults are fixed before others. The prioritisation rules that we investigate are discussed in section 5.6.1 when we introduce three prioritisation schemes for predictive maintenance.

3.5 Predictive maintenance and Telstra's current system

Before it could implement a predictive maintenance scheme Telstra would need to modify its current fault management system. Modifications that would need to be made are:

- Not all lines connected to an AXE exchange should be tested. Only the lines of active customers. Non-active customer lines will never be reported as faulty by customers so they should not be tested for predictive maintenance purposes.
- Current FM/FB data is not adequate for predictive maintenance as data can be missing when an AXE exchange rejects a request to access its buffer. This needs to be addressed so that FM/FB data is always available. If not always available it is impossible to know if a line is no longer FM/FB or if that line has not been accessed from the buffer.
- The frequency that FM/FB buffers are accessed needs to be increased. If Telstra are to fix a fault before a customer detects the problem it must respond to FM/FB data as quickly as possible.
- DIRECTOR needs to be modified to assign faults based on prioritisation rules that are discussed in section 5.6.1.

Chapter 4

Analysis of fault mark (FM) and fault block (FB) data

Before a predictive maintenance scheme can be implemented Telstra must have the ability to accurately predict which faults customers will report in the future. In this chapter we analyse Telstra's FM/FB data and examine its potential to be used in a predictive maintenance scheme. Specifically we will be trying to answer the following questions: How accurately does FM/FB data predict future TRs? How can the ability of FM/FB data to predict future TRs be improved? What percentage of TRs can be predicted? How quickly do customer TRs arrive after a line has first become FM/FB? How consistently do FB lines appear over a 48 hour period? And is there a relationship between the number of times a line is FB and the ability to predict future TRs?

4.1 The "predictive power" of FM/FB data

If Telstra is to use FM/FB data for predictive maintenance it needs to know how accurately it can predict future TRs. We have called the percentage of FM/FBs that correctly predict future customer TRs the *predictive power*. Predictive power is defined to be the percentage of FM/FB lines that customers report within 3 weeks of first observing a FM/FB. As an example, if there are 20 different FM/FB lines and customers report 15 of these lines as faults some time in the next 3 weeks then the predictive power is 75%. The specification of 3 weeks is assigned on the basis that the probability of a predicted TR arriving after 3 weeks is less than 2%¹.

If using FM/FB data for predictive maintenance, a high predictive power means that there is a greater chance a FM/FB line will predict a future customer TR. If FM/FB lines can be fixed quickly enough, then a high predictive power means there is a greater chance a customer fault will be fixed before that customer detects and reports it. In terms of the aims of this thesis, this will help to reduce TR volume, although it may or may not increase the maintenance workload. In order for Telstra to get the greatest benefit from using FM/FB data for predictive maintenance it must have predictive power as high as possible.

4.1.1 Identifying characteristics to improve predictive power

In June 1998 Telstra received an average of 6119 FM/FB lines per day. Of these only 556 correctly predicted a customer TR, giving a predictive power of 9.1%. In order to improve the predictive power of FM/FB data the lines that are most likely to predict a

¹ Refer to section 4.3 for details on this analysis.

customer TR need to be identified. This can be done by querying FM/FB data to identify characteristics of lines that are most likely to predict future TRs.

During a meeting with Telstra's David Aitken, Ross Bird and Murray Blackwell [15], nine distinct characteristics were chosen for investigation. These characteristics are summarised in Figure 4.1. Starting with a combined FM/FB data set three groups can be created: the original Combined FM/FB group, a FM group and a FB group. Each of these groups are queried to identify lines that are domestic customers. The domestic customers in each group are queried to identify lines that are within a range of 30 o-pairs of each other. An o-pair number is the number assigned to a customer line at a pillar. Therefore lines that are within a 30 o-pair range are likely to be located close to each other. If there is a fault on two or more lines that are within a 30 o-pair range, Telstra believes it is likely these faults are caused by a common problem and can possibly be fixed by a single field worker.

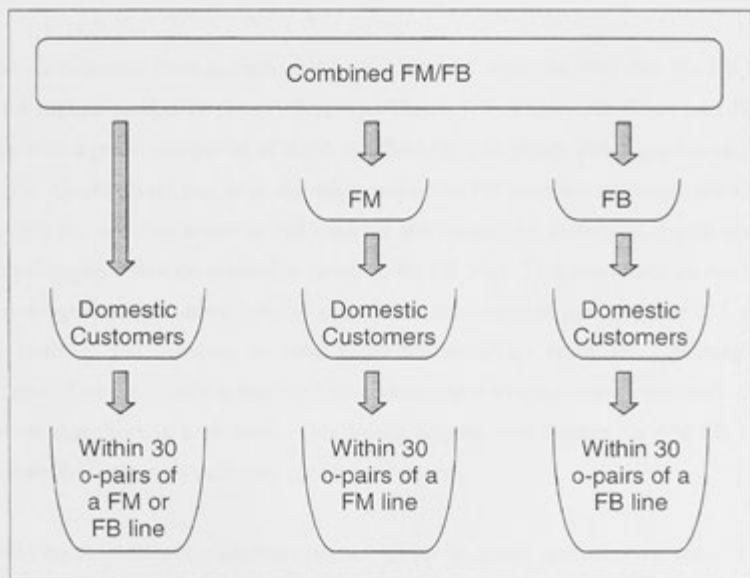


Figure 4.1: The separation of FM/FB data into groups with specific characteristics.

For this analysis a selection of FM/FB and TR data was taken from 1/6/98 to 3/7/98 and 1/6/98 to 30/7/98 respectively. After querying the FM/FB data to obtain groups with the

desired characteristics each group is compared with the TR data to determine that groups predictive power. The results are shown in Figure 4.2.

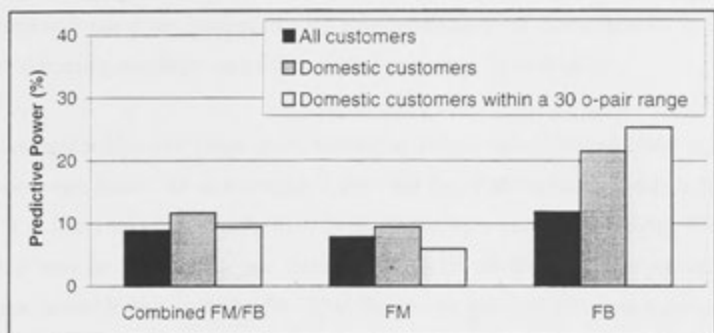


Figure 4.2: The predictive power of different characteristics of FM/FB data. On the x-axis are the three groups of data. On the y-axis is predictive power. The characteristics are given in the legend.

When *all customer* lines in each group are compared it can be seen that the FB group has the highest predictive power of 11.8%. This is followed by the Combined FM/FB group with a predictive power of 8.5% and then the FM group with a predictive power of 7.7%. Qualitatively this is as we might expect as FB lines are disconnected and are definitely not working where as FM lines are still connected. However, quantitatively it is surprising how low the predictive power is for FB lines. This result tells us that out of 100 disconnected customers only 11 report their disconnected line in the next 3 weeks. This leads to the question of why aren't the other 89 customers reporting their problems? One possibility is that the 89 customers haven't tried to use their lines and are unaware that there is a problem. This would suggest that Telstra are FM/FB testing customer lines that aren't actively used by customers.

Identifying the domestic customers in each group improves predictive power to 11.6%, 9.4% and 21.5% for Combined FM/FB, FM and FB respectively. However, identifying domestic customers in each group that are within a 30 o-pair range produces mixed results. For Combined FM/FB, and FM this results in a reduced predictive power of 9.4% and 5.9% respectively. However, in the case of FB lines the predictive power

increases to 25.3%. It is not clear why the individual FB and FM data sets perform so differently to the application of this characteristic.

From this analysis it can be seen that the best combination of characteristics is FB lines that are domestic customers and within a 30 o-pair range of each other.

We have used a 30 o-pair range characteristic, as Telstra believes it may help to identify common cause faults. As an example, if there are five FM/FB faults within a 30 o-pair range it is likely these five faults have been caused by a common problem. When this occurs it may be possible for one field worker to fix all five faults by correcting the common cause. In this case the five FM/FBs can be grouped into one ticket of work (ToW). A ToW is a job assignment that field workers receive from DIRECTOR². We make the assumption that two or more FM or FB domestic lines that are within 30 o-pair of each other can be grouped to create one ToW.

One advantage of grouping FM and FB lines to a single ToW is that one worker can fix a single problem that may be a common cause to many faults. If one or more FM/FB lines that make up a ToW correctly predict a future TR then we say the ToW has correctly predicted a TR. Therefore, the predictive power of ToWs can be calculated by counting the percentage of ToWs that predict at least one customer TR. The predictive power of ToWs is calculated and can be seen in Figure 4.3.

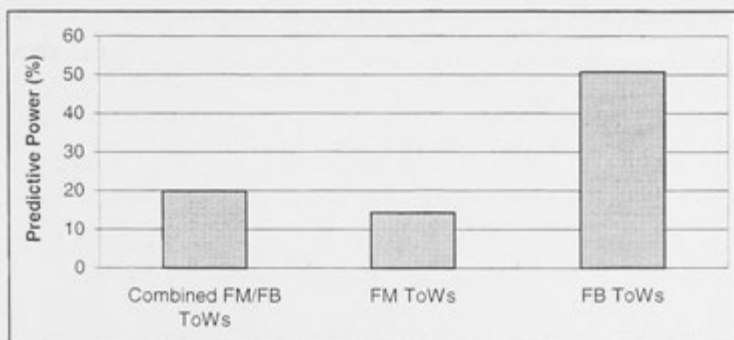


Figure 4.3: Predictive power of the tickets of work (ToWs) for each group. Each group is on the x-axis and predictive power is on the y-axis.

It can be seen in Figure 4.3 that FB ToWs have the highest predictive power of 50.7%. The Combined FM/FB ToWs have the next highest predictive power of 19.9% and the FM ToWs perform the worst with a predictive power of 14.3%.

Counting domestic FBs that are within a 30 o-pair range as a single ToW has doubled the predictive power of this group. The reason is that we are no longer directly matching individual FBs with TRs. We are now matching a group of FBs with TRs, which means that a group of two or more FBs can predict a single TR.

From the analysis so far it could be assumed that based on predictive power alone, FB ToWs are the best to use for predictive maintenance. FB ToWs are more than twice as likely to prevent a future TR from occurring than Combined FM/FB ToWs and more than three times as likely to prevent a future TR than FM ToWs.

4.2 What percentage of the daily TR volume can be predicted?

An important question to ask before implementing a predictive maintenance scheme is what percentage of existing TRs can be predicted and possibly prevented? One of the performance measures used in this thesis is TR volume. Therefore we want to find the potential reduction in TR volume that may be attained by using FM/FB data for predictive maintenance. We will look at ToWs as well as each group without any characteristics to determine the percentage of daily TRs they predict. The data used in this study had a daily average of approximately 3000 customer TRs. The results can be seen in Figure 4.4.

² Telstra's automated fault despatch system.

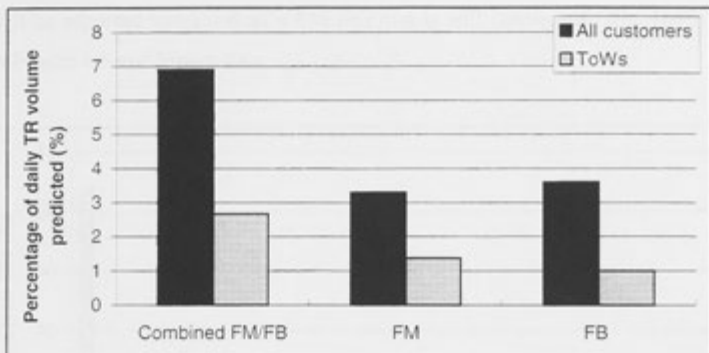


Figure 4.4: Percentage of daily TR volume predicted by each group. The groups are on the x-axis and the percentage of daily TR volume predicted is on the y-axis. The characteristics of the groups are given in the legend.

It can be seen in Figure 4.4 that the ToW characteristic results in 2.7%, 1.4% and 1% of daily TRs predicted by the Combined FM/FB, FM and FB group respectively. When all customers in each group are counted the percentages rise to 6.9%, 3.3% and 3.6% respectively. Therefore if Telstra's primary goal is to reduce TR volume it may choose to use all customers in the Combined FM/FB data group as it has the greatest potential to reduce the TR volume, even though it has a poor predictive power of 8.5%. On the other hand Telstra may wish to be selective with its maintenance and use FB ToWs as they have the greatest predictive power, but the least capacity to reduce the daily TR volume.

4.3 Analysis of the delay between the arrival of a FM/FB and the arrival of the predicted TR

The purpose of this analysis is to determine the time that elapses between a line becoming FM or FB and the predicted TR arriving. For proactive maintenance purposes this time is important, as it is the time that maintenance crews have to fix a FM or FB line if they want to beat a customer to a fault, and therefore prevent a TR from arriving.

This analysis uses FM/FB data from the 1/6/99 to the 10/7/99 as well as TR data from the 1/6/99 to the 31/7/99. The analysis has been divided into two groups, FM lines and FB lines. The reason for this is that as FB lines are disconnected it is intuitive to think

they will be reported quicker than a FM line that is still connected. The results can be seen in Figure 4.5 and Figure 4.6.

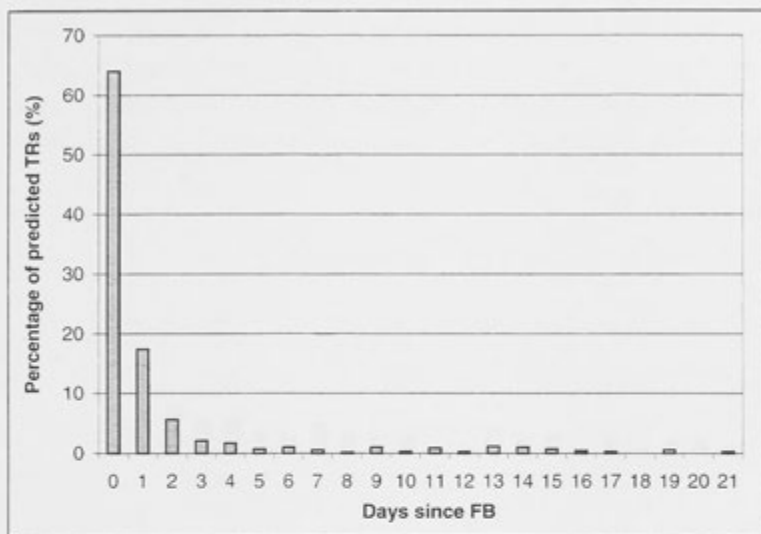


Figure 4.5: The percentage of predicted TRs that arrive each day after they are first predicted by FB data. On the x-axis is the day in which the predicted TR arrives after the line becomes FB and on the y-axis is the percentage of the predicted TRs that arrive each day.

From Figure 4.5 it can be seen that 64% of predicted TRs arrive within 24 hours of the FB and 81% will arrive within 48 hours. Therefore, if Telstra is to use FB data to predict future customer TRs it must react very quickly to FB alarms. In order to react quicker to FB alarms the current practise of obtaining FB data three times per day needs to be changed so that FB data is received as close to real time as possible.

However, a point to consider is that as FB data arrives closer to real time it is possible that Telstra will end up reacting to intermittent faults (lines going in and out of FB status). Another consequence might be that Telstra would be back operating in a reactive mode. It has already been mentioned that this is undesirable as maintenance becomes unplanned and many common cause faults are not detected resulting in poor utilisation of the workforce. Clearly a balance needs to be found so that FB lines can be

fixed as quickly as possible while still maintaining a planned and effective maintenance system that is able to detect common cause faults.

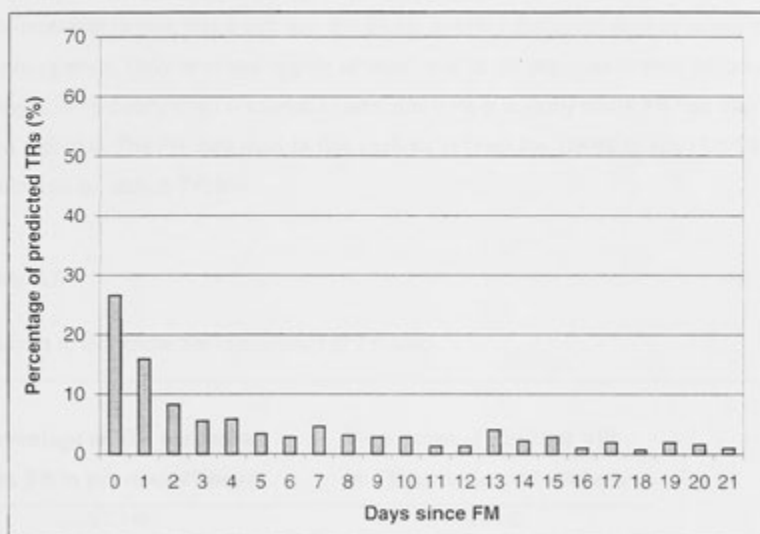


Figure 4.6: The percentage of predicted TRs that arrive each day after they are first predicted by FM data. On the x-axis is the day in which the predicted TR arrives after the line becomes FM and on the y-axis is the percentage of the predicted TRs that arrive each day.

From Figure 4.6 it can be seen that 26% of predicted TRs arrive within 24 hours of the FM and 42% will arrive within 48 hours. Comparing Figure 4.5 with Figure 4.6 it can be seen that FM data provides the best chance to fix faults before customers report them, even though FMs have a lower predictive power. This also gives Telstra more time to wait for other FM lines so it can possibly detect common cause faults.

4.4 Analysis of the consistency of FB lines

A question that has developed during this study is how come the number of FB lines is so high (an average of 1509 distinct lines per day) yet the number of TRs relating to them is so small? One possible answer could be that FB lines are not remaining FB for an extended period of time. For example there may be intermittent FB lines that appear

one day and disappear the next. This section aims to determine the percentage of FBs that appear more than once over a 48 hour period.

It is important to note that a line may not be FB in every sample of data observed over a 48 hour period. Only lines that appear *at least once* in the previous or next 48 hours are counted. A 48 hour period is chosen as after this time it is likely that a FB line may have been repaired. The FB data used in this analysis is from the 1/6/98 to the 11/6/98. The results can be seen in Table 4.1.

Table 4.1:

Analysis to determine the consistency of FB lines

Percentage of FBs that have been FB in previous 48 hours	Percentage of FBs that will be FB again in next 48 hours
87.1%	87.1%

From Table 4.1 it can be seen that an average of 87.1% of FB lines had been FB in the previous 48 hours. It can also be seen that 86.7% of FB lines were FB in the next 48 hours. From this we may conclude that the stability of the FB data is good. This tells us that there are very few FB lines that appear once in a 48 hour period. The implication is that Telstra can be confident that if it responds to an initial FB, it will not be fixing an intermittent fault that may quickly disappear.

4.5 Analysis of the relationship between the number of times a line is FB and the predictive power

This analysis is undertaken to determine if the number of times a line is FB is related to the probability of it becoming a TR. We have taken 13 consecutive FB data collections from 1/6/98 to the 5/6/98 inclusive. The FB lines are categorised according to the number of times each line appears as FB. The predictive power of each group is calculated and the results can be seen in Figure 4.7 and Figure 4.8.

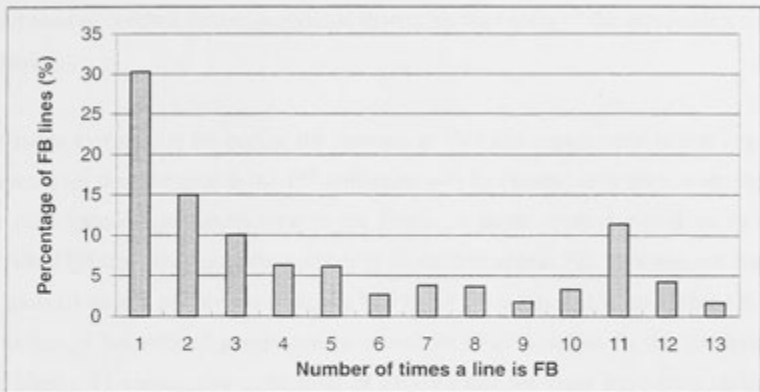


Figure 4.7: The percentage of FB lines found in each category. On the x-axis is the number of times a line is FB (maximum 13). On the y-axis is the percentage of FBs that are in each group.

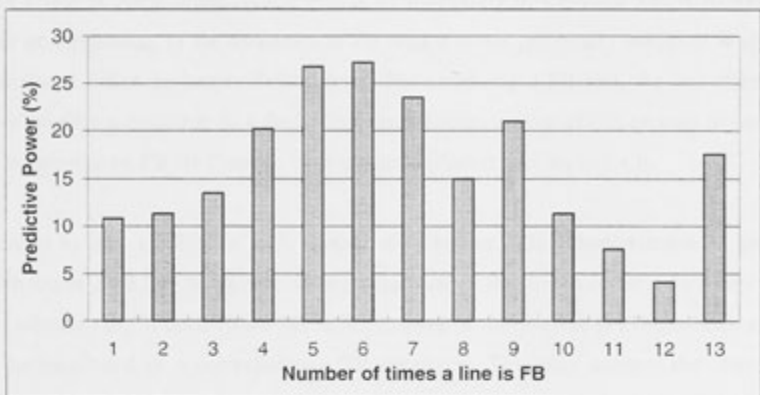


Figure 4.8: Predictive power of each group. On the x-axis is the number of times a line is FB (maximum 13). On the y-axis is the predictive power of each group.

Figure 4.7 shows that approximately 30% of FB faults that appear over 13 consecutive collections of data appear only once. This is not consistent with the results in Table 4.1, which indicate that approximately 13% of FBs should appear only once. Immediately this raises questions about the validity of the data we have used in this chapter. Before Telstra could implement a predictive maintenance scheme based on FM/FB data it

would need to conduct further analysis to determine the causes of the inconsistencies we are seeing.

A possible explanation for part of the increase in FBs that appear once is that any FBs appearing for the first time in the 13th collection will be counted only once, even though they may appear again some time in the future. A better method would be to track individual FB lines and count the number of times they appear FB. This was not done in this analysis as it is not always clear if a line is not FB because it is no longer FB or if the exchange has refused permission to access its FM/FB buffer. In this analysis we have chosen 13 consecutive collections of FB data that we know have been collected. Therefore, if a FB does not appear in this collection we know that it was not FB when that collection was taken.

It can be seen in Figure 4.8 that predictive power is the greatest at approximately 27% when a line is FB 6 times. While this is an interesting observation and it provides a better understanding of the dynamics of FB data it is not practically useful. It is shown in section 4.3 that the longer Telstra wait after observing a FB line, the less chance it has of beating a customer to a fault. Therefore Telstra cannot afford to wait to see if a line is going to be FB six times or twelve times before it decides to fix it.

Figure 4.8 also exhibits a bell shaped distribution. This demonstrates a greater likelihood of a FB line being reported by a customer if that line is observed in more than one collection of FB data. However, as the number of times a line is FB increases above six the likelihood of a corresponding TR decreases. This may suggest that there are many lines that are not actively used by customers. These lines are constantly tested and reported as FB. Testing and storing these lines in buffers is a waste of resources and can affect the predictive power of FB data. For example, if there are 20 FB lines and 5 are reported as TRs then predictive power is 25%. However if 5 of the 20 FB lines are disconnected and not used by customers then they should be discarded from predictive power calculations. Discarding these lines leaves 15 FB lines and 5 TRs, which increases predictive power to 33%.

4.6 Summary of FM/FB data analysis

The analysis conducted in this chapter reveals that before Telstra could implement a predictive maintenance scheme with FM/FB data it needs to resolve a number of problems. These are:

- The results in section 4.1.1 show that the predictive power, when counting all FB lines, is 11.8%. This suggests that Telstra is FM/FB testing lines that are not actively used by customers. As FB lines are disconnected from the network any customer trying to use a FB line will definitely be aware of the problem. As they cannot use their phone they will most likely report this problem. Testing FM/FB lines that are not actively used by customers is a waste of system resources. Such lines occupy space in the FM/FB buffer and require periodical testing. To rectify this Telstra needs to be able to specify which lines are FM/FB tested by AXE exchanges.
- In light of the idea that Telstra is possibly testing lines that are not actively used by customers it is hard to draw a conclusion as to the effectiveness of FM data. As FM lines are still connected Telstra needs to identify the physical properties of lines that will be reported as faulty by customers. Further investigation is required to determine if insulation resistance alone is adequate or if Telstra needs to apply other tests to more accurately predict lines that will be reported by customers in the future.
- Further research could also be conducted into optimal FM and FB insulation resistance settings. Currently these are set by Telstra at 50k Ω and 20k Ω respectively however it is not clear what impact changing these settings would have.
- Throughout this analysis we were hampered by the fact that FM/FB data is very inconsistent in its appearance. As AXE exchanges can reject the request to download the contents of their FM/FB buffers it is impossible to determine if a line is intermittently going in and out of FM or FB status or if it is just not being collected. Until this can be resolved Telstra's understanding of FM/FB dynamics will be limited and its potential for predictive maintenance not realised.
- Another area for further investigation is why do lines leave FM or FB status. Presuming that the FM/FB buffer in an AXE exchange could be accessed, we do not

know why lines go in and out of FM or FB status. Is Telstra fixing these lines or are the lines somehow correcting themselves? If they are correcting themselves what is causing this?

- Finally, an alternative for Telstra could be to find or develop new predictive technology. It may be possible for Telstra's switches to perform other tests that may improve the results we have seen so far.

Modeling Telstra's Call Minutes-to-Speak System

Chapter 5

Modelling Telstra's CAN Maintenance System

5.1. System architecture

5.1.1. Overview of the system architecture

The system architecture is shown in Figure 5.1. The system is divided into three main components: the user interface, the business logic, and the data storage. The user interface is responsible for providing the user with a means of interacting with the system. The business logic is responsible for processing the user's requests and performing the necessary actions. The data storage is responsible for storing the system's data.

The user interface is implemented using a web browser. The business logic is implemented using a set of services. The data storage is implemented using a database.

5.2. Modelling the system architecture

The system architecture is modelled using a set of diagrams. The first diagram is a use case diagram, which shows the user's interactions with the system. The second diagram is a class diagram, which shows the system's classes and their relationships. The third diagram is a sequence diagram, which shows the system's execution flow.

After analysing the existing system, we need to experiment with it to determine operating conditions that satisfy the goals of this study. One method of doing this is to establish a system model. A system model enables the analyst to observe the performance of the system under different operating conditions. This chapter discusses the method that we have used to establish a model of Telstra's CAN maintenance system that we will use in chapter 6 to evaluate system performance. The performance measures that are used in the simulation analysis are presented along with the maintenance priority schemes. Finally we discuss why simulation is used to evaluate the performance of our model and how this is achieved.

5.1 System modelling - the first step

"System modelling is the first step toward understanding how an existing system actually works" [4]. A system model provides a means of approximating the true behaviour of a real system. If a model is accurate, then its approximation of behaviour is very close to true behaviour. As we strive to understand a system of interest we often want to study the system under different conditions, for example, different parameter values or different input functions. Using a system model is often cheaper and less time consuming than changing and studying a real system. System models may be mathematical equations, laboratory reproductions of a real system or computer simulation. The type of model used will depend upon the aims of the analysis and the experience of the modeller.

There are many ways of classifying systems such as static or dynamic, time-varying or time-invariant, linear or non-linear, continuous-state or discrete state, time-driven or event driven, deterministic or stochastic and discrete time or continuous time. The reader is referred to [4] for further reading on each of these system classifications.

5.2 Classifying a model of Telstra's CAN maintenance system

Depending on the aims of the analysis a system may be modelled in many different ways. In this work we want to identify the operating conditions that reduce the TR volume, maintenance workload and mean TR system time when using a predictive maintenance scheme. Telstra's CAN maintenance system can be thought of as a queuing system where faults (FM/FBs and TRs) arrive in the system and wait in a queue until a worker is available to fix them. Using a queuing system we are able to count the number

of TRs that arrive in the system (TR volume) as well as the number of FM/FBs and TRs that need to be fixed (maintenance workload). If we record the time when a TR enters and exits the system then we are also able to calculate the mean TR system time. As a result we have chosen to model Telstra's CAN maintenance system as a discrete event queuing network. Queuing systems are often found in our daily lives when, in order to use certain resources, we have to wait. A simple one server queuing system can be seen in Figure 5.1.

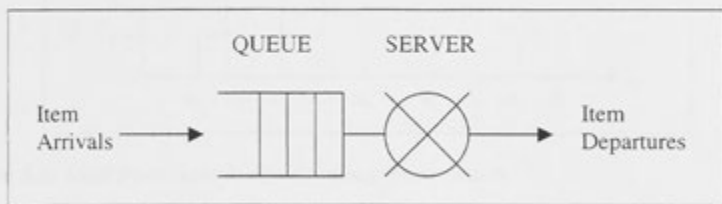


Figure 5.1: A single server queuing system

In terms of Telstra's CAN maintenance system, each arriving item is a fault (FM/FB or TR) that needs to be fixed. The server is a field worker who will fix faults enabling them to depart from the system. A queuing system is used because it effectively represents the main procedures that occur in Telstra's CAN maintenance system. For example, faults arrive in the system when they are reported by customers, the faults have to wait in a queue until a field worker is available to fix them and then once fixed they exit the system. Another reason for modelling Telstra's CAN maintenance system as a queuing system is that the rate of customer TR arrivals can easily be determined as well as the rate at which field workers fix faults. These parameters are essential inputs for a queuing system. Other information required to classify a queuing system is the queue type and its capacity. These are discussed in section 5.6.

The state of a queuing system is often defined to be the length of the queue. Therefore, a change in a system's state occurs when an item arrives or departs from the queue. This is called a state transition. If we denote a_i to be the arrival of the i th fault and d_i to be the departure of the i th fault then an example of how Telstra's CAN maintenance system changes state can be seen in Figure 5.2.

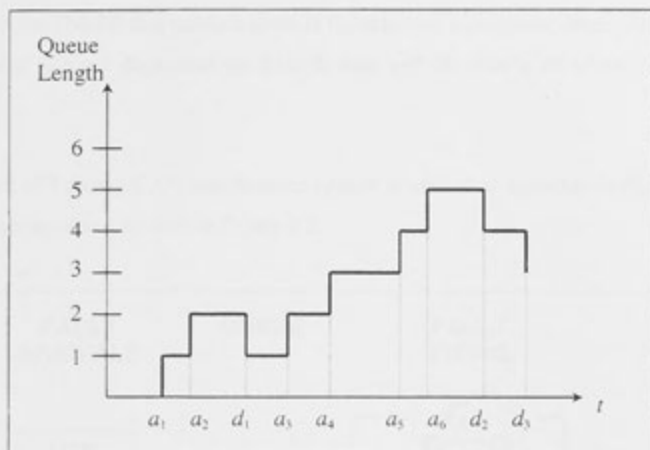


Figure 5.2: State transitions in a fault management system.

As the state can only take discrete integer values it is said to be a discrete-state system. Also, as the state is changed by asynchronously occurring instantaneous events such as fault arrivals or fault departures it is said to be an event driven model. Randomness in nature is something that affects all real life systems. In Telstra's CAN maintenance system this means the rate at which faults occur and the rate at which customers report them is non-deterministic. It also means the performance of field staff will vary from person to person, as well as from job to job. As a result the state of the system can only be described probabilistically, and the system is called a stochastic system. Combining these characteristics, our model of Telstra's CAN maintenance system falls into the classification of a *stochastic discrete event system*.

This thesis aims to determine operating conditions that reduce the TR volume, reduce the maintenance workload and reduce the mean TR system time when a predictive maintenance scheme is used. Therefore we need to model the arrival of FM/FB data in Telstra's CAN maintenance system. There is a connection between FM/FBs and TRs as some FM/FBs predict future TRs. Quickly fixing these FM/FBs can prevent the predicted TRs from arriving. To model this characteristic we have decided to use two types of TR classifications, Predictable TRs (PTRs) and Unpredictable TRs (UTRs). UTRs can not be prevented and are independent of FM/FB data. They represent instantaneous faults such as cut cables, or network outages. PTRs can be prevented from

arriving if the FM/FB that predicts them is fixed before a customer detects the problem. Therefore PTRs are dependent on FM/FB data and the timing of when FM/FBs are fixed.

A diagram of Telstra's CAN maintenance system modelled as a stochastic discrete event queuing network can be seen in Figure 5.3.

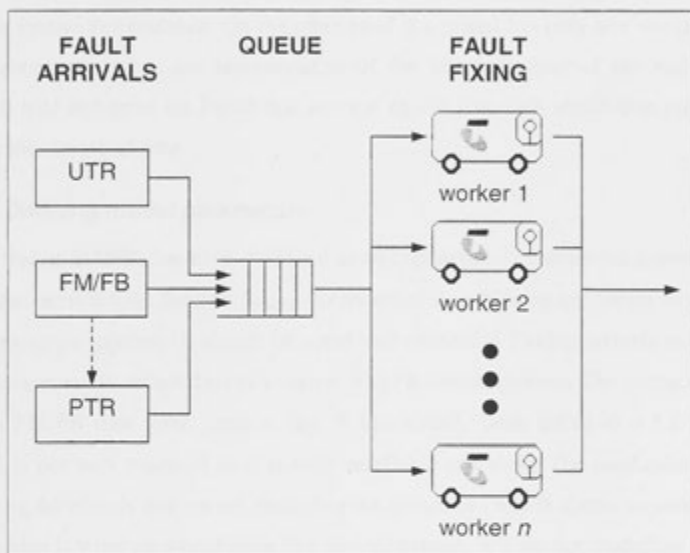


Figure 5.3: System model of Telstra's CAN maintenance system. The broken arrow between FM/FB and PTR does not represent the flow of faults. The broken line indicates that a correct FM/FB will trigger the generation of PTRs.

5.3 Modelling the field staff and the fault fixing process

It is a natural phenomenon that some people work faster than others and some jobs take longer than others. In order to model these influences we have decided to assign each of the five workers in our model Erlang- k distributed service times. The process of fixing a fault is composed of many phases such as driving to the customer's house, setting up testing equipment, locating the fault and fixing the fault. We are not concerned with the actual steps involved in each task, only that each task takes some length of time. Considering the time to complete each task to be exponentially distributed enables us to use an Erlang- k distribution to model the overall time to fix the fault. Each worker, $i =$

1, 2, ... n , has a mean time to fix a fault μ_i , and a number of phases k . The shape of an Erlang- k distribution demonstrates the property that some jobs may take less than the mean time, but never less than zero, while some jobs may take considerably longer than the mean.

We have decided to set $n = 5$. This number is chosen to keep the model at a manageable size. If a model has too many workers it requires more calculations and takes longer to evaluate system performance. On the other hand if a model has only one worker then it is too simplistic and is not representative of the true behaviour of the real system. Through trial and error we found that when n equals five each simulation run takes a manageable length of time.

5.4 Defining model parameters

The arrival of FM/FBs has been modelled as an exponentially distributed process with a mean inter-arrival time denoted $\theta_{FM/FB}$. Exponential distributions are commonly used to model an arrival process. It should be noted that modelling FM/FB arrivals in this way does not accurately reflect Telstra's current FM/FB arrival process. The current process collects FM/FB data three times a day. It has already been stated in 3.3.2 that this method is not very practical as it is both unreliable and slow. The implication of our modelling decision is that we are modelling the arrival of FM/FB alarms as soon as they occur which is what we would want in a *desired* system. We are not modelling Telstra's current FM/FB arrival process as we are not trying to analyse the performance of Telstra's current system. We are trying to determine operating conditions that reduce the performance measures of interest using a predictive maintenance scheme.

The arrival of customer TRs has also been modelled as an exponentially distributed process. In the case of UTRs, an exponentially distributed inter-arrival time with a mean denoted θ_{UTR} is used. As these TRs are unpredictable their arrival process is independent of any other processes. However PTRs by their definition are dependent upon FM/FBs.

We define three parameters that can be used to describe the relationship between FM/FBs and PTRs. The first parameter we call the predictive power and we denote it PP . The second parameter relates to the ability of FM/FB data to detect faults that are

caused by a common problem. Typically a mean number of TRs from different customers will arrive relating to a single common problem. We call this parameter the mean number of common cause TRs per correct FM/FB and we denote it β . In this work we have used integer exponential distributions with means of $\beta = 1, 2, 3$ and 4^3 . These values for β were arbitrarily chosen for simplicity, however an analysis of FM/FB and TR data could possibly find means and distributions that accurately reflect the behaviour of the real system. We do not use a single distribution obtained from Telstra's real system as we do not want to determine the performance of Telstra's current system. We use four different distributions so that we can observe and understand the effects that variations in β have. The third parameter is the time between the arrival of a FM/FB and the arrival of the PTR that it predicts. The distribution we have used can be seen in Appendix B.

5.4.1 Calculating the mean UTR inter-arrival time

We have modelled our system by firstly specifying the number of workers in the model. We denote the overall mean time that faults are fixed by the maintenance system (the five workers) as Θ . If we denote μ_i as the mean time that worker i takes to fix a fault then we can calculate the overall mean time to fix a fault as

$$\Theta = \left[\sum_{i=1}^n \frac{1}{\mu_i} \right]^{-1} \quad (5.1)$$

Where,

n = the number of workers in the model.

So that we can specify the mean UTR inter-arrival time we make the assumption that without any predictive maintenance the mean number of TRs that arrive each day is equal to the mean number of faults that are fixed by the system each day. This helps to simplify our model as we are not able to change the number of workers in the model.

If we denote $\#_{TOTAL}$ as the mean number of TRs generated per unit time, $\#_{UTR}$ as the mean number of UTRs generated per unit time, $\#_{PTR}$ as the mean number of PTRs

³ Refer to Appendix A for the distributions of the β values.

generated per unit time and $\#_{FM/FB}$ as the mean number of FM/FBs generated per unit time then we can write

$$\#_{UTR} = \#_{TOTAL} - \#_{PTR} \quad (5.2)$$

Now

$$\#_{PTR} = \#_{FM/FB} \cdot PP \cdot \beta \quad (5.3)$$

Where,

PP = the predictive power

β = the mean number of common cause TRs per correct FM/FB

Therefore we can write

$$\#_{UTR} = \#_{TOTAL} - (\#_{FM/FB} \cdot PP \cdot \beta) \quad (5.4)$$

Converting the notation to units of time we have

$$\frac{1}{\theta_{UTR}} = \frac{1}{\Theta} - \frac{PP \cdot \beta}{\theta_{FM/FB}}$$

Or

$$\theta_{UTR} = \frac{(\Theta \cdot \theta_{FM/FB})}{(\theta_{FM/FB} - \Theta \cdot PP \cdot \beta)} \quad (5.5)$$

Where,

$$\theta_{FM/FB} > \Theta \cdot PP \cdot \beta$$

Equation (5.5) is the defining equation of this model, and it is a unique contribution of our work as we have established a relationship between FM/FB data and TRs that has not been understood up until this stage. From equation (5.5) there are four operating regions that the modelled system can take. These are listed below and can be seen in Figure 5.4.

Region 1: $PP = 0 \quad \therefore \theta_{UTR} = \Theta$.

In this case no FM/FBs predict future TRs. Therefore, all TRs are UTRs.

Region 2: $\theta_{FM/FB} = \Theta \cdot PP \cdot \beta \quad \therefore \theta_{UTR} = \infty.$

This state can not be practically reached as there cannot be an infinite amount of time between UTR arrivals. However in reality this means that there are no UTRs and all TRs are predicted by FM/FB data. In this region it is possible to prevent all of the TRs if the FM/FB faults are fixed before customers detect the faults.

Region 3: $\theta_{FM/FB} < \Theta \cdot PP \cdot \beta \quad \therefore \theta_{UTR} < 0.$

A negative mean inter-arrival time is physically impossible. This case corresponds to FM/FB data predicting more TRs than would normally appear. This is an impossible state for our model to take.

Region 4: $\theta_{FM/FB} > \Theta \cdot PP \cdot \beta \quad \therefore \Theta < \theta_{UTR} < \infty.$

This is the operating region that we will be operating in. It extends from region 1 to region 2.

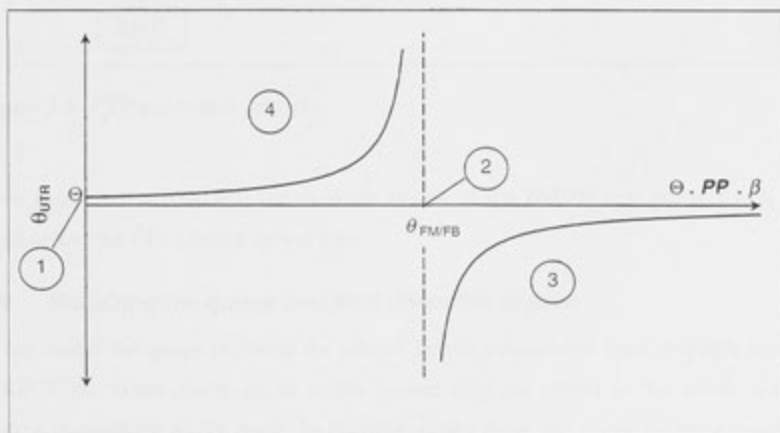


Figure 5.4: Different operating regions of equation (5.5)

5.5 Modelling the relationship between FM/FB and PTR

Unlike UTRs and FM/FBs, the arrival process of PTRs does not have a specified distribution and mean inter-arrival time as the arrival of PTRs is dependent upon the arrival of FM/FBs and whether or not the FM/FB that predicts them has been fixed. As

a result no closed form representation of the PTR arrival process exists. The PTR generation process is the sequence of decisions and events that are required to generate PTRs when a FM/FB arrives. This process can be seen in Figure 5.5.

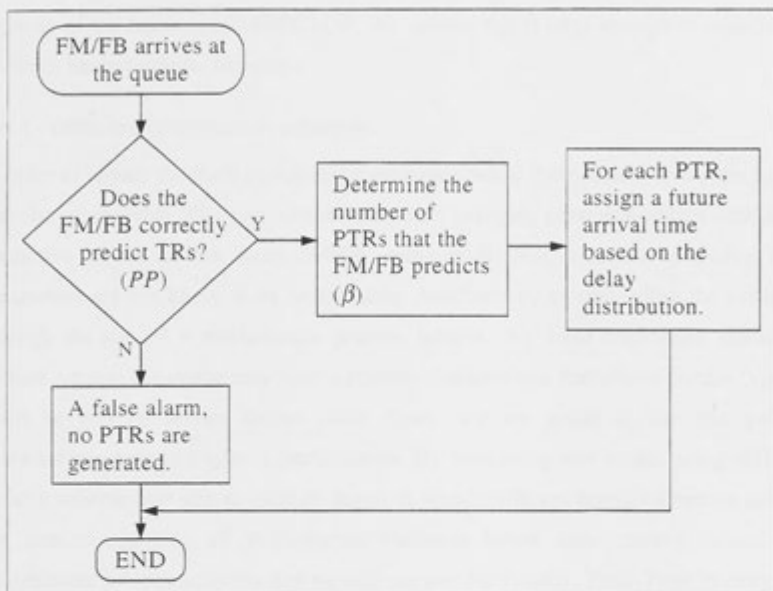


Figure 5.5: PTR generation process

Once generated, a PTR will arrive in the system if the FM/FB that predicts it is not fixed before the PTRs future arrival time.

5.6 Modelling the queue and fault despatch system

In our model the queue performs the role of Telstra's automated fault despatch system DIRECTOR. When faults arrive in the system they are stored in the queue until a worker is available to fix them. In queuing theory there are many different types of queuing classifications according to which items get served first. The most common type of queue is a First In First Out (FIFO) queue. Other queue types are Last In First Out (LIFO) and priority queues. Priority queues operate on the premise that there are two or more types of items that arrive, each type with an assigned a priority level. When an item arrives at the queue its priority determines where it is placed in the queue. Items with the highest priority will be placed at the front of the queue and items with the

lowest priority get placed at the back. For our work we use both FIFO and priority queues. However, unless it is explicitly stated it should be assumed that the queue is FIFO. We also assign the queue an infinite capacity, which means that the queue will never be full. In Telstra's maintenance system the queue length is limited by the capacity of the memory of DIRECTOR. We assume this is large enough to consider the queue as having infinite capacity.

5.6.1 Different prioritisation schemes

In order to reduce the three performance measures below their current levels the system must be controllable. This control can come from changing parameter values such as the predictive power or the mean FM/FB inter-arrival time, however in reality these parameters are not likely to be controllable. Another way of controlling the system is through the use of a maintenance priority scheme. We have mentioned already in section 5.6 that the queue may have a priority characteristic that allows certain types of faults to receive service before other types. We are going to use this priority characteristic to study system performance. By simulating our model using different priority schemes we aim to identify points at which different priority schemes achieve the aim of reducing all performance measures below their current values. The maintenance priority schemes that we will use are: No Priority, Fault-Type Priority, and Estimated Time to Fix (ETF) Priority.

The No Priority maintenance scheme is a simple FIFO queue. The first fault that arrives in the queue will be the first fault fixed. The FIFO queue does not identify different types of faults.

The Fault-Type Priority operating scheme assigns a level of priority to each fault type. In our model we have two types of faults, TRs and FM/FBs. Therefore, if we assign TR priority then any TR that arrives will go to the front of the queue ahead of any FM/FB faults. However if there are already other TRs in the queue it will be the last TR in the queue. This is illustrated in Figure 5.6.

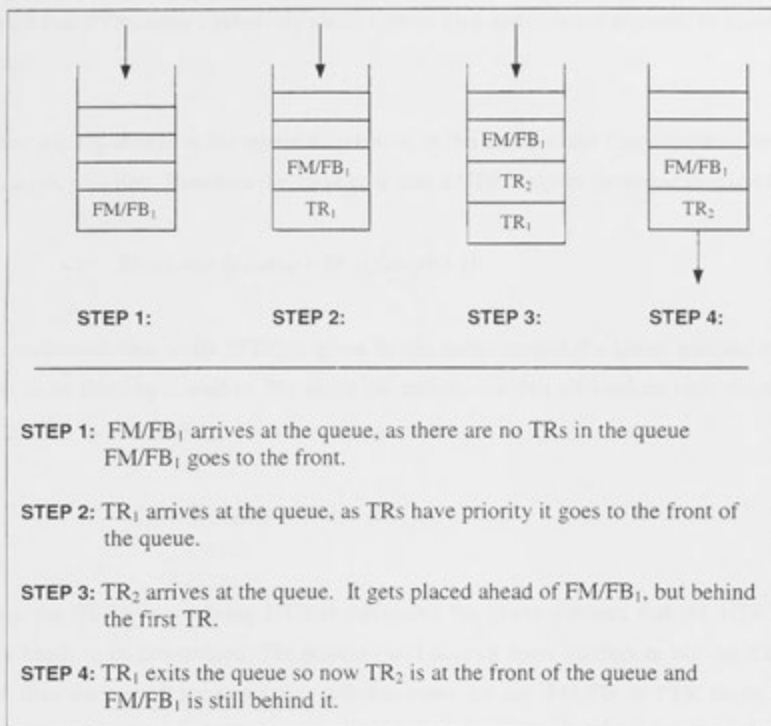


Figure 5.6: Example of a TR priority queue

The ETF Priority scheme prioritises faults based on whether the system time of a customer TR is likely to be greater than a predefined cut-off time. This scheme is motivated by the fact that although the mean time to fix TRs may be low, there may be many TRs that have a system time greater than an acceptable value. It is also motivated by the fact that Telstra has a legal obligation, as set out in its Customer Service Guarantee (CSG) [22] to fix a customer TR within a specified time. This time varies from metropolitan to remote areas. However if Telstra does not meet the CSG then it must compensate that customer. Gilchrist [6] reports that Telstra's annual CSG compensation bill could be as high as \$70 million in 2000.

It is decided to prioritise only UTR faults in the ETF Priority scheme. It will be shown in section 6.2 that PTRs can be fixed when the FM/FB that predicts them is fixed. This

means that PTRs have a relatively small system time and it is not required to prioritise them.

When a UTR arrives at the queue its position in the queue is the current queue length, $QLength$, plus one. Therefore the mean time that a UTR waits in the queue is given by

$$\text{Mean time in queue} = \Theta \cdot (QLength + 1) \quad (5.7)$$

The estimated time to fix (ETF) is given by the mean time in the queue plus the mean time to be fixed by a worker. We make the assumption that all workers have the same mean time to fix a fault, μ . Therefore we can write

$$ETF = \Theta \cdot (QLength + 1) + \mu \quad (5.8)$$

Once the ETF of an arriving UTR is calculated the queue position that the UTR will take needs to be determined. The position will depend upon whether or not the ETF is less than the cut-off time and also whether there are any FM/FB or PTR faults with ETFs less than the cut-off time. It can be seen in Figure 5.7 that every queue will have a certain number of positions that will have an ETF less than the cut-off time and the rest will be greater or equal to the cut-off time.

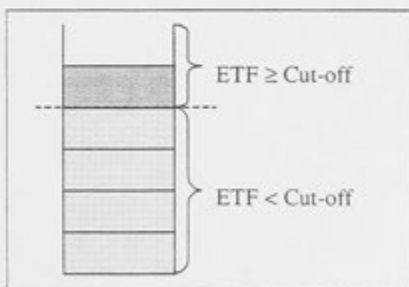


Figure 5.7: Illustrating the cut-off point in every queue. All faults in the light grey area will have ETFs less than the cut-off time. All faults in the dark grey area will have ETFs greater than or equal to the cut-off time.

If upon arrival a UTR has an ETF less than the cut-off time, it will not be prioritised and will be placed at the back of the queue. This means that all items in the queue will meet the cut-off and no prioritisation is required. However, if the arriving UTR has an ETF greater than or equal to the cut-off then its position in the queue will depend on the types of faults that are ahead of it in the queue. The decision process we use to decide on the placement of an arriving UTR is illustrated in Figure 5.8.



Figure 5.8 Decision process for placement of an arriving UTR based on the priority of the arriving UTR.

The decision process for placement of an arriving UTR is shown in Figure 5.8.

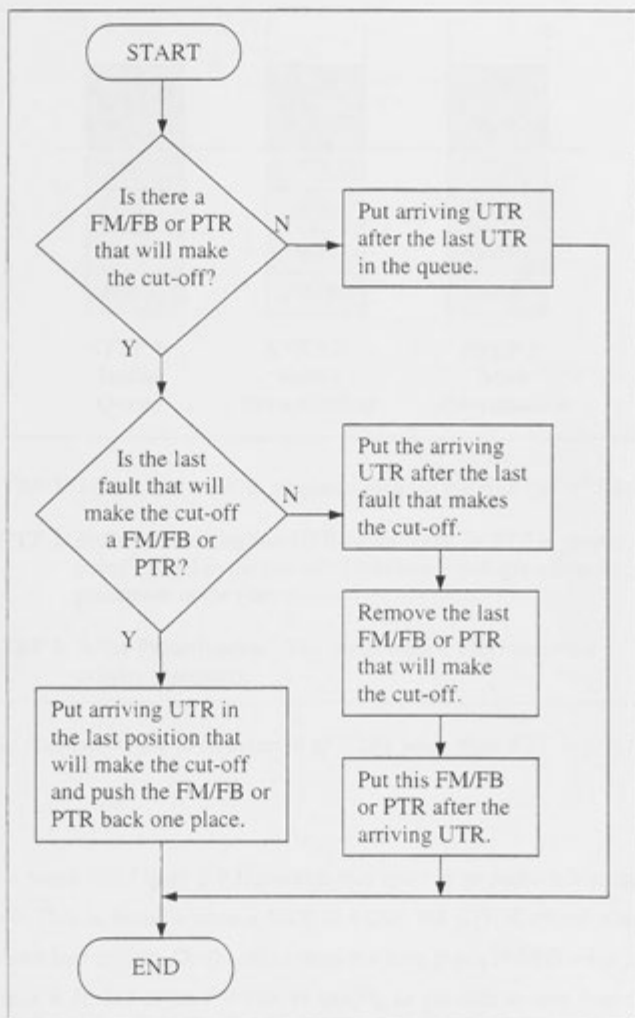


Figure 5.8: Decision process to prioritise an arriving UTR with an ETF greater than or equal to the cut-off

This decision process is explained graphically by the example given in Figure 5.9.

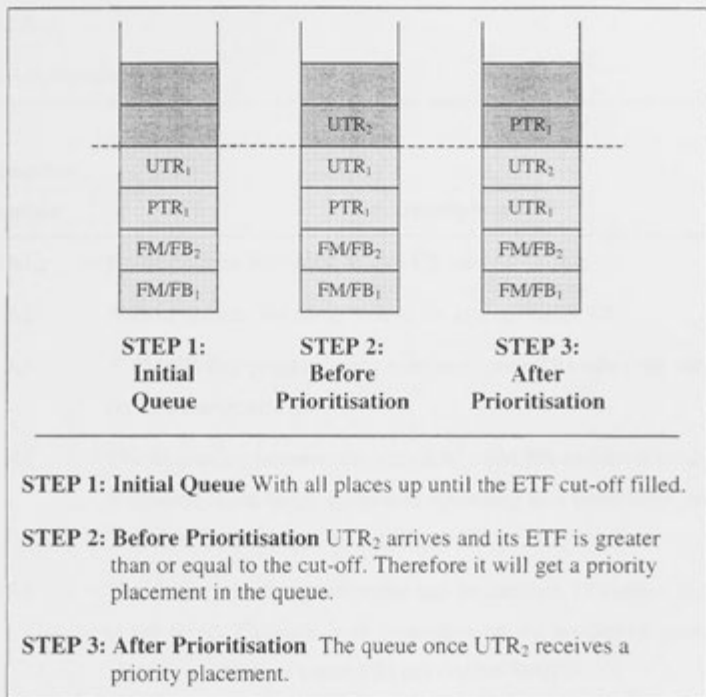


Figure 5.9: Example of the prioritisation of UTRs when their ETF is greater than the cut-off.

It should be noted that Figure 5.9 highlights that there is no relative sorting within the cut-off zone. This is because once a UTR is within the $ETF < \text{cut-off}$ zone, the time until it is fixed isn't critical. On the other hand the time that a FM/FB waits in the queue is critical as it is desired to fix FM/FBs as quickly as possible so that future PTRs may be prevented. A FM/FB fault will only be moved out of the $ETF < \text{cut-off}$ zone if it is the last (closest to the back of the queue) FM/FB in the $ETF < \text{cut-off}$ zone and there is a UTR arriving that will miss the cut-off.

5.7 Model assumptions

In order to evaluate the model's performance under different operating conditions various assumptions about its behaviour need to be made. The assumptions used throughout this study are given in Table 5.1.

Table 5.1:

Model Assumptions

Assumption	
Number	Description
A1	No distinction between FM and FB has been made.
A2	A FM/FB takes the same time to fix as a customer TR.
A3	A FM/FB that predicts many common cause TRs takes the same time to fix as a customer TR.
A4	The time delay between the arrival of a FM/FB and the arrival of the TR it predicts is randomly generated according to a predefined distribution. This distribution is given in Appendix B.
A5	The rate at which unpredictable and predictable TRs arrive in the model is not fixed. They are both dependent on the predictive power and the number of common cause TRs per correct FM/FB.
A6	All five workers have the same mean time to fix a fault, μ , and same k value.

In our model we treat a FM fault the same as a FB fault (A1). This assumption is made to keep the model simple so that only one predictive power and one mean number of common cause TRs per correct FM/FB are required. This is not a limitation of the model and it can be changed so that two distinct classes of prediction data are generated.

The assumptions that a FM/FB takes the same time to fix as a customer TR, whether it predicts multiple common cause TRs or not (A2 and A3), are also made to simplify the modelling and simulation. It is not known whether these assumptions are correct as Telstra does not currently fix FM/FB faults. However when a FB is reported by a customer, the time taken to fix that TR could reasonably be assumed to be the same as the time taken to fix the FB.

Assumption A4 means that the delay distribution is fixed and does not change throughout this study. It should be noted that the distribution used was not obtained from the analysis in section 4.3 as the analysis was not completed at the time the simulation analysis began. The distribution we use was obtained from a preliminary analysis of the delay between FM/FB and the TRs they predict. Although the distribution we use is not identical to either of those obtained in section 4.3, it is similar to the delay between FMs and the TRs they predict shown in Figure 4.6.

The assumption that the rate at which PTRs and UTRs arrive in the model is not fixed is an important one. It is believed that in Telstra's network there is an underlying level of UTRs that arrive which cannot be predicted. These faults are such things as cable cuts or accidents that disrupt the supply of Telstra's service. However in our model we are not constrained by such things. Depending on the predictive power and the mean number of common cause TRs per correct FM/FB, it may be possible to predict all customer TRs.

The assumption that all five workers have the same mean time to fix a fault, μ , and same k value (A6) is made to simplify the analysis. This is a reasonable assumption which means we measure the mean service time per worker, not the mean service time of each worker.

5.8 Performance measures

The performance of any system will be measured differently according to the aims of the analysis. For example a Telstra customer may measure the performance of Telstra's CAN maintenance system as the average time they must wait to have their fault fixed once the fault has been reported. However Telstra shareholders may not be concerned with such a measure and are more likely to measure the performance as the overall cost of CAN maintenance.

In either case a key performance indicator, or performance measure, is required so that each group can quantitatively calculate the system's performance. Performance measures provide a way of comparing the performance of different systems or comparing the performance of the same system under different conditions. For example the performance of a maintenance system with 4 workers and a FIFO queue may be

compared to the performance of a maintenance system with 5 workers and a LIFO queue. Based on the respective performances a decision can be made as to which system performs better.

It is important to carefully choose what is measured as performance measures usually drive system behaviour. For example if field worker performance is measured only by the number of faults fixed per day then we may find that field staff are only concerned with fixing faults as quickly as possible. This may result in the field staff neglecting to follow standard procedures, which results in rework of the same fault at a later time. The performance of a queuing system can be measured by the *mean waiting time* of items, the *mean system time* of items or the *mean queue length*. Mean waiting time is the mean time an item spends waiting to be served in the queue. Mean system time is the mean time an item spends waiting in the queue plus the time it takes for that item to be served. The mean queue length explains itself. It is desirable to have all of these measures as small as possible. Other queuing system performance measures that are desirable to have as large as possible are the *utilisation* of the servers and the *throughput*. Utilisation is the fraction of time a server is busy. A high utilisation means that the servers are used efficiently. Throughput is the number of items served over a defined period of time. It is usually desirable to serve as many items as possible so that throughput is maximised.

One of the motivations of predictive maintenance is to increase customer satisfaction. Customer satisfaction is very hard to measure, however it can be related to two things. Firstly a customer will be dissatisfied if they detect a fault with their service. Secondly, once they have detected the fault and reported it their dissatisfaction will increase with the length of time they must wait to have their service fixed. Therefore, customer dissatisfaction can be measured by the number of TRs that Telstra receive, or the *TR volume*, and the mean system time of customer TRs, or the *mean TR system time*. Predictive maintenance involves fixing both customer TRs as well as FM/FB faults. As a result we need to measure the workload of the field staff to ensure that predictive maintenance does not create more work than they currently have. Therefore the third performance measure is defined to be the *maintenance workload*, which is the number of faults, both FM/FB and TRs that arrive in the system which have to be fixed by field staff.

It will be shown that the performance measures are related to each other as changing the performance of one can affect the performance of the others. For example if the TR volume is reduced it may be the case that this also reduces the maintenance workload as well as the mean TR system time. However, it will be shown that this will not always be the case. The actual variation in the performance of the other measures is a function of the predictive power, the mean number of TRs predicted by a correct FM/FB and the maintenance priority scheme used.

A fourth measure that will be used in section 6.3 is the number of TRs that have a system time greater than a predefined cut-off time. This measure is designed to count the number of times Telstra misses a CSG obligation.

5.9 Simulating the model of Telstra's CAN Maintenance System

Real world systems do not always yield a set of equations that, when solved, accurately describe a system's behaviour. Often random influences make a model too complex to solve analytically. In such cases model performance may be *estimated* numerically by computer simulation. Computer simulation is analogous to a laboratory experiment with computer software capturing all of the physical interactions. The randomness, or noise, that is found in real systems is incorporated into computer simulation via software called a random number generator. Computer simulation is a popular tool as it is often unrealistic to build a real system in a laboratory and too risky to invest time and money into constructing a real world system based on a "gut feeling". As a result systems such as manufacturing systems, telecommunication networks and commuter traffic networks are all commonly modelled and analysed using computer simulation. However, simulation is not the real thing and any results are only estimates of true system behaviour.

We simulate our model using a commercially available simulation package called Extend™. There are many simulation packages available however Extend™ was chosen for a number of reasons. Firstly it is user friendly and available for both PC and Macintosh computers. Another feature is the accessibility of its software code that enables the user to modify the code of the model. Also, compared to similar simulation packages Extend™ was relatively cheap which also contributes to our decision to use it.

An example of Telstra's CAN maintenance system modelled in Extend™ is shown in Figure 5.10.

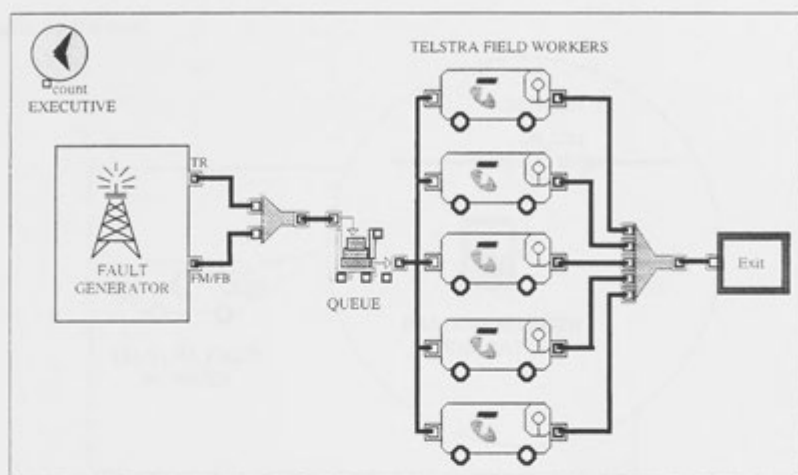


Figure 5.10: Telstra's CAN maintenance system modelled in Extend™

Extend™ models flow from left to right. Therefore, faults are generated randomly in the Fault Generator block and immediately go to the Queue where they wait until a Telstra field worker is available to fix them. Finally the faults exit the system at the Exit block. The block in the top left hand corner, called the Executive block, is required in all discrete event models in Extend™. The Executive block keeps track of the overall system time, so that events occur in the correct sequences, and the simulation ends at the specified time or event. The Queue block is a priority queue in which the user can specify the capacity. For our purposes we want the queue to have infinite capacity so we set the capacity at 1,000,000. As this capacity is never reached it is effectively an infinite capacity queue. The Exit block (far right) is used to remove faults from the system once a Telstra field worker has fixed them.

The Fault Generator block and the Telstra field workers are called *hierarchical* blocks in Extend™. They are composed of smaller blocks whose functionality combine to achieve the task of the larger block. It can be seen in Figure 5.11 that the modelled

Telstra field workers consist of a server and a random number generator. The length of time that the server takes to complete a job before passing it to the Exit block is determined by the random number generator. In our model the random number generator uses an Erlang-k distribution with the mean service time μ and parameter k input by the user.

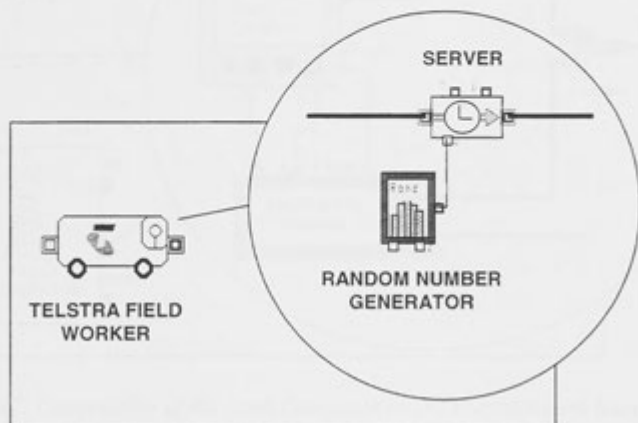


Figure 5.11: Composition of the Telstra field worker block. The thick dark lines pass faults into and out of the server. The thin line passes the service time from the random number generator block to the server.

It can also be seen in Figure 5.12 that the Fault Generator block is made up of four smaller blocks: a UTR Generator, a FM/FB & PTR Generator, a Fault Rate Calculator and a Combine block. These blocks have been specifically coded for this project and are not standard Extend™ blocks that are built into the package.

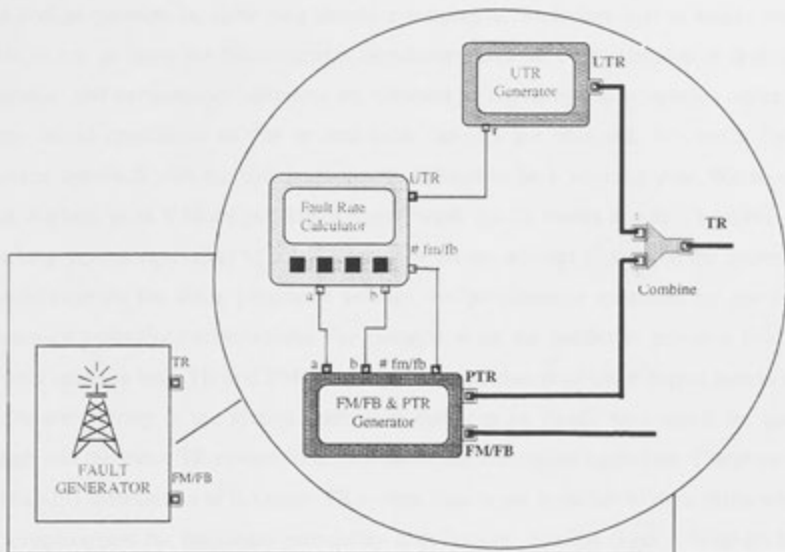


Figure 5.12: Composition of the Fault Generator block. The thick dark lines pass faults from the UTR generator and the FM/FB & PTR generator blocks. The thin lines pass values for PP , β , $\theta_{FM/FB}$, and θ_{UTR} .

Values for predictive power, PP , the mean number of common cause TRs per correct FM/FB, β , and the mean inter-arrival time of FM/FB faults, $\theta_{FM/FB}$, are input in the FM/FB & PTR Generator block. These values are passed to the Fault Rate Calculator through the 'a', 'b' and '#fm/fb' connectors respectively. The value of the overall mean time that faults are fixed, Θ , is input in the Fault Rate Calculator block. Using Θ , along with PP , β and $\theta_{FM/FB}$, the mean UTR inter-arrival time, θ_{UTR} , is calculated using equation (5.5) and input to the UTR Generator through the 'r' connector.

The length of time that a simulation runs depends on the type of output analysis performed. There are two kinds of output analysis: steady state and finite-horizon. Steady state analysis estimates parameters of various stationary probability distributions (ie distributions that maintain their dynamic behaviour invariant to time shifts). In steady state analysis there is no obvious point to end the simulation as it is desired to observe the system's behaviour as $t \rightarrow \infty$. However, a finite-horizon simulation is one whose length is defined by a time or a state of the system. In steady state simulations

the critical question is: How long should a simulation run before it is at steady state? This is not an issue for finite-horizon simulation. Instead, every simulation defines a "sample" and performance estimates are obtained by repeating the simulation under the same initial conditions so that several such samples are obtained. We use a finite-horizon approach with the simulation length defined to be 1 working year. We assume that workers work 8 hours per day, 6 days a week for 52 weeks a year. Therefore one working year is equivalent to 2,496 hours. We do not attempt to analyse the system in steady state as for some parameter settings the performance measures do not have stationary probability distributions. For example when the predictive power is 0%, the system receives both TR and FM/FB data. The combination of these inputs means that faults are arriving in the system faster than they can be fixed. As a result the queue length and the mean TR system time increase as the simulation continues. Therefore the probability distribution of the mean TR system time is not invariant to time shifts which is a requirement for stationary probability distributions. In such cases a finite-horizon analysis still enables a comparison of system performance.

5.10 Summary of modelling Telstra's CAN maintenance system

In this chapter we have modelled Telstra's CAN maintenance system as a stochastic discrete event queuing network. A comprehensive illustration of this model is given in Figure 5.13.

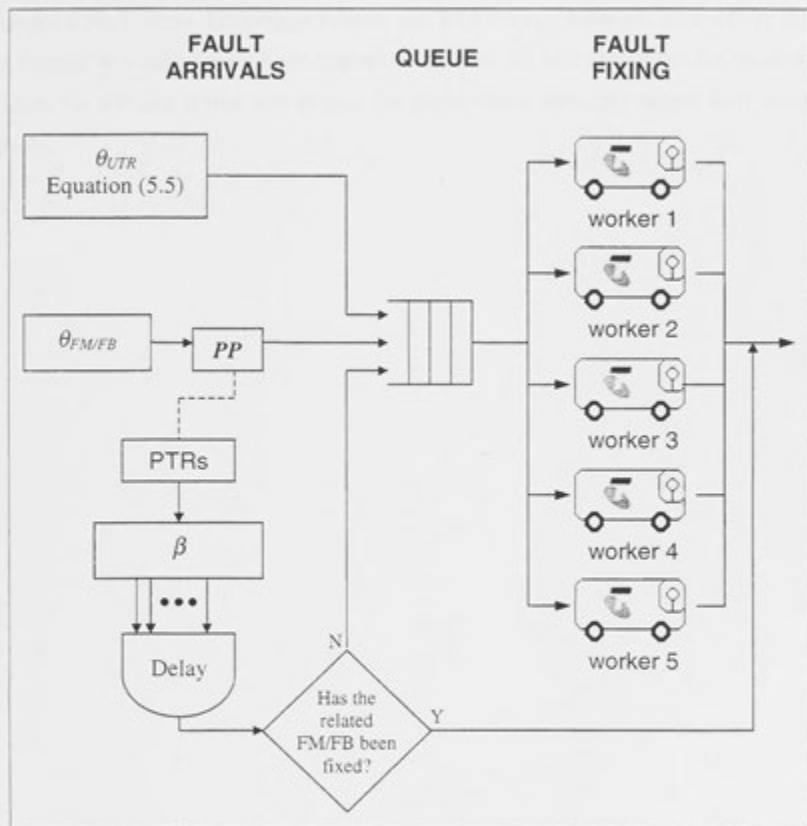


Figure 5.13: A comprehensive model of Telstra's CAN maintenance system. The broken line connecting PP and $PTRs$ does not represent the flow of FM/FB faults. The broken line indicates that a correct FM/FB will trigger the generation of $PTRs$, the number of which depends on β .

We have established a unique relationship between FM/FBs and TRs that is captured by equation (5.5). This equation allows us to calculate the mean UTR inter-arrival time, θ_{UTR} , when given values for PP , β , $\theta_{FM/FB}$ and μ .

Using the assumptions given in Table 5.1 we are able to evaluate system performance using the No Priority, Fault-Type Priority and ETF Priority schemes. This will be done in chapter 6 when, for each prioritisation scheme, we will determine the minimum values for PP and β that will reduce the performance measures below their current levels.

Chapter 6

Identification of operating conditions that improve system performance

In this chapter we use simulation to examine ways in which Telstra can improve the performance of its CAN maintenance system. Specifically we determine operating criteria that achieve the cycle of operation shown in Figure 1.2, which was one of the aims of this thesis. We do this by conducting 3 sets of experiments. The first examines the performance of Telstra's CAN maintenance system if Telstra does not identify which TRs are predicted by which FM/FBs. When this happens PTRs are not cleared with the FM/FBs that predict them. The second experiment studies the effect of clearing PTRs with the FM/FBs that predict them. In both of these experiments the maintenance priority scheme, predictive power and β that result in the best system performance are identified. The importance of understanding the sensitivity of performance to variations in predictive power is examined when we show that a 3% decrease in predictive power may result in a 38 hour (4.75 day) increase in mean TR system time. The third experiment demonstrates how an Estimated Time to Fix (ETF) Priority scheme can be used to reduce mean TR system time as well as reduce the number of TRs that have a system time greater than a predefined value. We show that it is possible for Telstra to reduce the number of times it violates a customer service guarantee (CSG) repair time by up to 96%.

In each experiment the predictive power is incremented in steps of 10%. Therefore, results are obtained for predictive powers of 0%, 10%, 20%, ..., 100%. For each value of predictive power the model is simulated ten times and the mean performance is calculated. The curves shown in the results are linear interpolations between these points.

6.1 Experiment 1: System performance when PTRs are not cleared with the FM/FBs that predict them

This experiment has the characteristic that it does not clear PTRs that have arrived when the FM/FB that predicts them is fixed. As this is the first experiment, the decision not to match FM/FBs with the PTRs they predict was made to keep the initial analysis simple. In a real system this is analogous to Telstra using FM/FB data without understanding the ability of FM/FB data to identify common cause faults. Therefore when a PTR and FM/FB have a common cause, the commonality is not recognised and the PTR and FM/FB are individually fixed. In this case the only benefit of predictive maintenance

comes from preventing future TRs by fixing FM/FBs before customers detect a problem.

The parameter values used in this experiment can be seen in Table 6.1.

Table 6.1:
Parameter Values

Parameter	Description	Value
Θ	The mean time that all faults (both FM/FBs and TRs) are fixed by the whole system (5 workers).	0.4 hours (20 faults per day)
μ	The mean time a worker takes to fix a fault.	2 hours
β	The mean number of common cause TRs per correct FM/FB.	1, 2, 3 or 4
$\theta_{FM/FB}$	The mean inter-arrival time between FM/FB faults.	0.8 hours (10 FM/FBs per day)
θ_{UTR}	The mean inter-arrival time between UTR faults.	Determined by equation (5.5)
k	The number of phases in an Erlang- k distribution.	7
PP	Predictive power.	0, 10, 20, ... 100%

6.1.1 Reducing TR volume

The first performance measure that we want to reduce is TR volume. An estimate of the current TR volume, 6240 TRs per year, is obtained by multiplying 20 TRs per day (the number of TRs fixed per day without FM/FB data) by 6 days a week, 52 weeks of the

year. Initially the model is run with a No Priority maintenance scheme. In Telstra's current system this scheme is equivalent to fixing TRs and FM/FBs on a First In First Out (FIFO) basis. We have set β equal to 2 which means that each correct FM/FB predicts two TRs. The results can be seen in Figure 6.1.

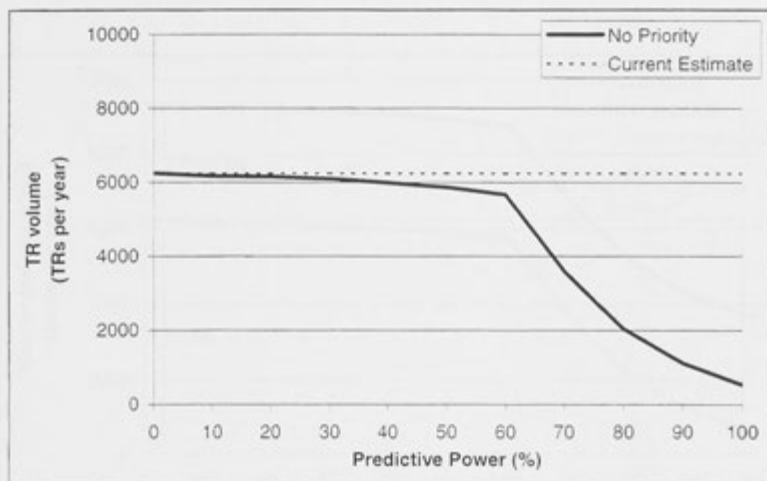


Figure 6.1: Predictive power required to reduce TR volume. On the x-axis is predictive power and on the y-axis is the number of TRs received per year. A No Priority maintenance scheme is used with a β of 2.

In Figure 6.1 the TR volume is reduced for all values of predictive power. For predictive powers between 0% and 60% the reduction in TR volume is quite small as there are many false alarms in the queue that do not predict future customer TRs. While these false alarms occupy system resources to get fixed, FM/FBs that correctly predict future TRs have to wait longer in the queue. By the time these correct predictions get fixed customers have already reported the faults (PTRs).

For predictive powers greater than 60% the TR volume drops significantly as more FM/FBs correctly predict future TRs. These correct FM/FBs are fixed sooner, before customers detect and report them as PTRs. This reduces the number of PTRs in the queue, which means that more FM/FBs are fixed sooner and fewer customers are reporting faults.

6.1.2 Reducing maintenance workload

Although TR volume is reduced for all predictive powers above 0%, we do not know what effect predictive maintenance has on maintenance workload. Figure 6.2 shows the maintenance workload for predictive powers between 0% and 100% when a No Priority scheme is used and β equals 2.

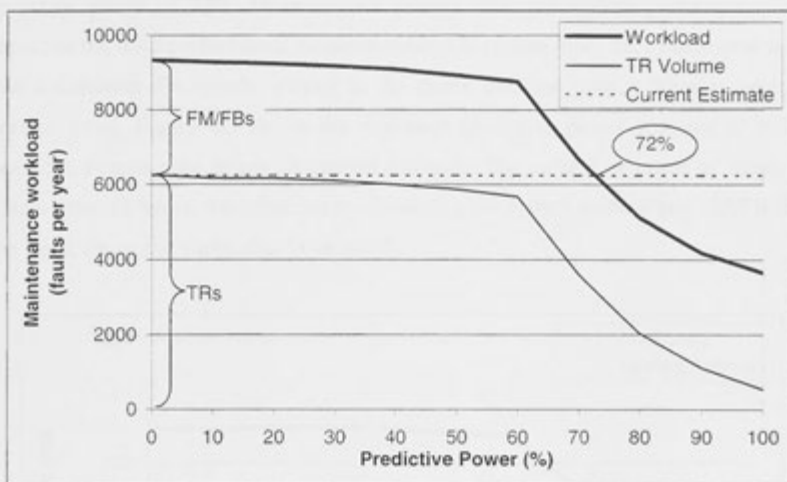


Figure 6.2: Predictive power required to reduce maintenance workload. On the x-axis is predictive power and on the y-axis is the number of faults to be fixed per year. A No Priority scheme is used with a β of 2.

It can be seen in Figure 6.2 that maintenance workload consists of customer TRs (both UTR and PTR) and FM/FB faults (including false alarms). In this experiment maintenance workload takes the same shape as the TR volume curve but is shifted vertically by the yearly FM/FB volume (10 FM/FB per day, or 3120 FM/FB per year). This is because we are not matching FM/FBs with the PTRs they predict. We are not identifying common cause faults that can be cleared by a single worker so all faults (FM/FBs, PTRs and UTRs) that arrive must be individually fixed.

The only advantage of operating such a scheme is observed when TRs are prevented by fixing the FM/FBs that predict them before customers detect the problems. In such cases it won't be until the TR volume is reduced by an amount greater than the FM/FB

volume that maintenance workload will fall below its current level. It can be seen that this occurs when predictive power is 72%.

6.1.3 Reducing mean TR system time

Results so far indicate the performance of Telstra's CAN maintenance system can be improved through the use of predictive maintenance when there is a minimum predictive power of 72%. However, we haven't observed system performance with respect to the third performance measure: mean TR system time. TR system time is the time a customer TR spends waiting in the queue plus the time it takes to be fixed (service time). Figure 6.3 shows the minimum predictive power required to reduce mean TR system time below its current estimate. The current estimate of mean TR system time, 12 hours, was obtained by simulating the system without any FM/FB data. The log scale on the y-axis should be noted.

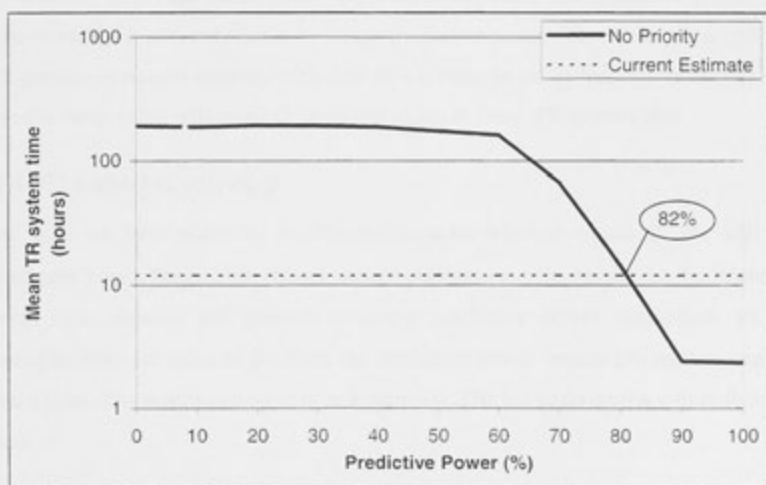


Figure 6.3: Predictive power required to reduce mean TR system time. On the x-axis is predictive power and on the y-axis is the mean TR system time in hours. A No Priority maintenance scheme is used with a β of 2.

Figure 6.3 shows that it isn't until a predictive power of 82% that mean TR system time falls below the current estimate. As with the TR volume and maintenance workload, it isn't until the predictive power is greater than 60% that the mean TR system time curve

begins to fall significantly. Again the reason is that after 60% more FM/FB faults are correctly predicting future TRs and these FM/FBs are fixed sooner which prevents PTRs arriving.

At predictive powers of 90% and 100% the mean TR system time is constant at approximately 2.4 hours. The mean service time to fix a fault is 2 hours so we can conclude that at these predictive powers the queue is predominantly empty and most arriving TRs are immediately sent to a field worker to be fixed.

For predictive powers between 60% and 90% the mean TR system time falls very sharply. This indicates that mean TR time is very sensitive to variations in predictive power over this range. As a result a small variation in predictive power could result in a large variation in mean TR system time. With respect to Telstra's maintenance system this is a very important observation. Telstra can not know the predictive power of its system exactly, it will only know the mean predictive power. Therefore when operating with predictive powers between 60% and 90% it must be aware that any variations away from the mean value will result in large variations in mean TR system time.

6.1.4 The effect of varying β

Until now we have observed system performance when β equals 2. We will now investigate how changing β effects model performance. In results so far mean TR system time requires the greatest minimum predictive power. Therefore, we will investigate how the value of β effects the predictive power required to reduce mean TR system time. The results can be seen in Figure 6.4. The log scale on the y-axis should be noted.

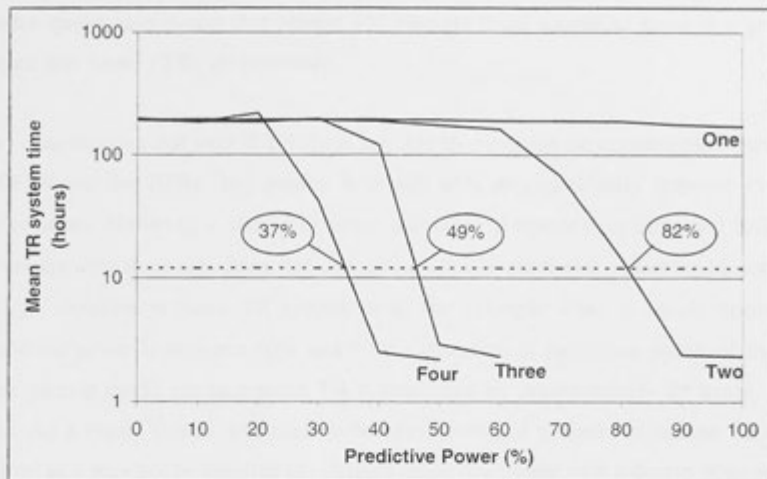


Figure 6.4: Predictive power required to reduce mean TR system time for different β . On the x-axis is predictive power and on the y-axis is the mean TR system time in hours. A No Priority maintenance scheme is used and each curve has been labeled with its β value.

From Figure 6.4, the mean TR system time when β equals one does not fall below the current estimate; in fact it barely changes. This is because even at high predictive powers, if Telstra does beat a customer to a fault, only one PTR is prevented. Saving one TR is not enough to significantly reduce the queue length, which means that TRs are waiting longer in the queue to be fixed. As this experiment does not clear PTRs with the FM/FBs that predict them, if we don't fix a correct FM/FB before a customer reports it there are two faults to fix, the PTR and the FM/FB. Hence the workload has doubled. This result highlights how important it is that Telstra can clear PTRs with the FM/FBs that predict them. If it can't do this then it could potentially be doubling its maintenance workload when β equals one.

When β equals two, three and four the mean TR system time falls below the current estimate at 82%, 49% and 37% respectively. In these cases many common cause TRs are prevented from arriving by fixing correct FM/FB predictions. When this happens the queue length is significantly reduced and TRs do not wait as long in the queue. The

shorter queue also means that correct FM/FBs get fixed sooner so there is a greater chance that future PTRs are prevented.

This demonstrates that even if Telstra is not able to recognise the commonality between FM/FBs and the PTRs they predict it is still able to significantly improve system performance. However, it should be noted that when β equals two, three and four the curves are very steep signifying that a small variation in predictive power could result in a large variation in mean TR system time. For example when β equals three and predictive power is between 40% and 50% a deviation in predictive power of two or three percent could increase mean TR system time by approximately 25 hours, or 3 days. As a result Telstra will need to be very careful if it wants to operate in these regions as it may not be possible to calculate predictive power with a degree of accuracy that eliminates such variations.

The curves for β equals three and four do not reach predictive powers of 100%. In fact they finish at 60% and 50% respectively. This is because at these values all of the TRs are predicted. For predictive powers greater than these values θ_{UTR} becomes negative which means the system is operating in region 3 as discussed in section 5.4.1.

6.1.5 Different maintenance priority schemes

So far all results have been obtained using a No Priority maintenance scheme which fixes faults on a FIFO basis. We will now investigate what effect a FM/FB Priority scheme and a TR Priority scheme have on system performance. Both FM/FB and TR Priority schemes are from the Fault-Type Priority scheme discussed in section 5.6.1. Figure 6.5 shows the predictive power required to reduce maintenance workload for different priority schemes when β is two.

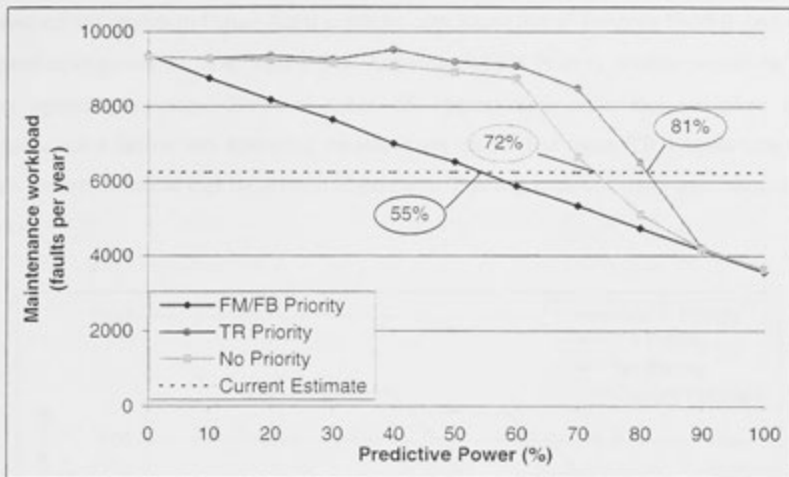


Figure 6.5: Predictive power required to reduce maintenance workload for each maintenance priority scheme. The x-axis is predictive power and the y-axis is the number of faults to be fixed per year. The different priority schemes are shown in the legend and β equals 2.

Figure 6.5 shows that the FM/FB Priority scheme is the best performing priority scheme, reducing maintenance workload below the current estimate at approximately 55%. The reason the FM/FB Priority curve is linear is that as FM/FBs are given priority, almost all correct FM/FBs are fixed before customers report the faults (ie before the PTRs arrive). Therefore maintenance workload consists of UTRs, FM/FBs and a small percentage of PTRs. The small percentage of PTRs that will always be present is discussed in section 6.2.1.

In Figure 6.5 No Priority is the second best scheme falling below the current estimate at 72%. The TR Priority is the worst performing scheme not falling below the current estimate until a predictive power of 81%. With a TR Priority scheme FM/FBs are waiting longer in the queue and aren't being fixed before customers report the problems. Also as we aren't matching FM/FBs with the PTRs they predict the PTRs that arrive have to be individually fixed which increases the maintenance workload.

Based on the results in Figure 6.5 it could be concluded that if Telstra's FM/FB data has a predictive power of 55%, with a β of 2, then a FM/FB Priority scheme would be the best operating strategy. However mean TR system time must also be taken into consideration before any operating decisions are made. The mean TR system time for each priority scheme can be seen in Figure 6.6. The log scale on the y-axis should be noted.

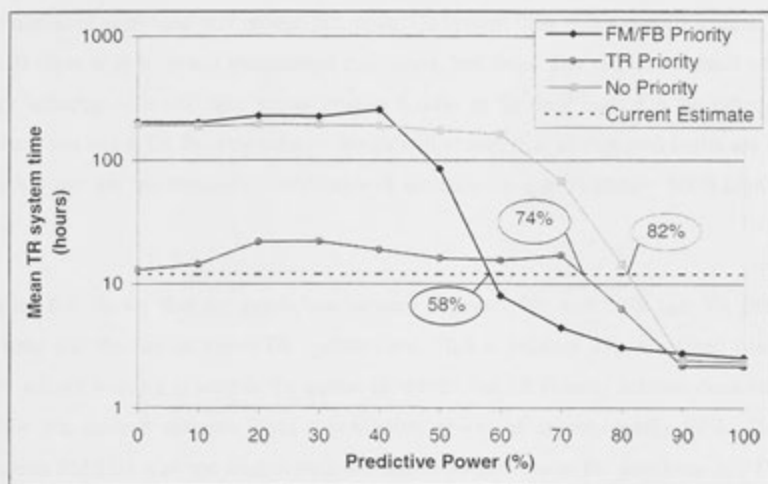


Figure 6.6: Predictive power required to reduce mean TR system time for each maintenance priority scheme. On the x-axis is predictive power and the y-axis is the mean TR system time in hours. The different priority schemes are shown in the legend and β equals 2.

Although a FM/FB Priority scheme will reduce the maintenance workload when predictive power is 55% it can be seen in Figure 6.6 that it would result in a mean TR system time of approximately 50 hours, or a little over 6 days. This is more than four times the current estimate of 12 hours. It isn't until predictive power is approximately 58% that mean TR system time falls below the current estimate. A very rapid decrease in mean TR system time occurs for a FM/FB Priority scheme with predictive powers between 40% and 60%. This shows that mean TR system time is very sensitive to a small change in predictive power over this range. As a result it would not be wise for

Telstra to operate in this range as a decrease in predictive power of 3% may result in an increase in mean TR system time of 38 hours.

This result demonstrates the importance of observing all system performance measures. It also raises the question of what is more important, dissatisfied customers or maintenance costs? For example, if Telstra has a predictive power of 55% then it has to choose its operating scheme. If it uses an FM/FB Priority scheme the TR volume and maintenance workload will reduce but mean TR system time will greatly increase. As a result there will be fewer dissatisfied customers, but those that do have a fault will be very unhappy as it will take approximately 6 days to fix their fault. On the other hand Telstra can use a TR Priority scheme which will ensure that all reported faults are fixed quickly but the maintenance workload will increase by approximately 3000 faults per year.

Figure 6.6 shows that for predictive powers between 0% and 57% the TR Priority scheme has the lowest mean TR system time. This is because TRs are fixed first and they are not waiting as long in the queue. However, the TR Priority scheme does not fall below the current estimate until a predictive power of approximately 74%. This is because FM/FBs wait too long to be fixed and customers report the problems as PTRs.

At a predictive power of 90% a TR Priority scheme has a slightly lower mean TR system time than the No Priority and FM/FB Priority schemes. The difference between the schemes here is approximately 1 hour. It is believed this is due to random noise in the results and is not significant. It should also be noted that at 90% all priority schemes have a mean TR system time of approximately 2 hours. This is the mean time to fix a fault, which implies that most TRs do not have to wait in the queue.

6.1.6 Experiment one conclusions

It was shown that the TR volume is reduced below its current estimate for all predictive powers greater than 0%. Intuitively this is what would be expected as predictive maintenance can only maintain or reduce TR volume, not increase it.

A summary of the predictive powers required to reduce the maintenance workload and mean TR system time below estimates of their current values when β equals 2 is shown in Figure 6.7.

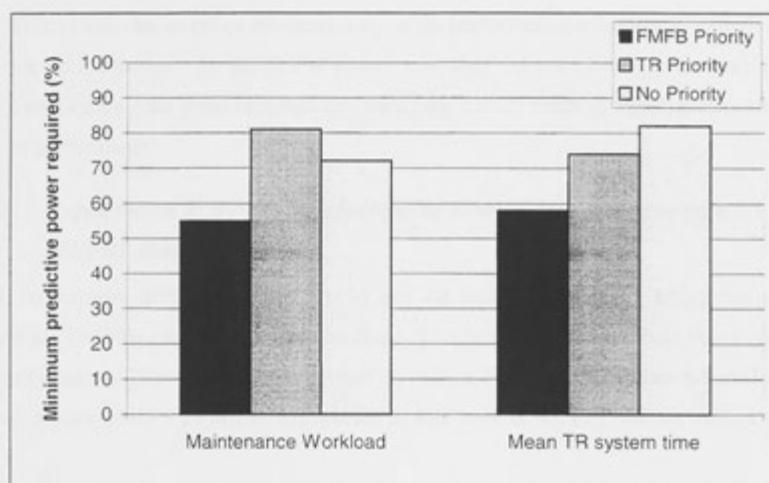


Figure 6.7: The minimum predictive power required to reduce each performance measure when β equals 2. On the x-axis is each performance measure and on the y-axis is the minimum predictive power that reduces the performance measure below the estimate of its current performance. The priority schemes are given in the legend.

From Figure 6.7 we can conclude that when β equals 2, a FM/FB Priority scheme will reduce all performance measures with the lowest predictive power of 58%.

The analysis conducted in this section has lead to the following conclusions:

- If Telstra is not able to identify which TRs are predicted by which FM/FBs the maintenance workload and mean TR system time increase as individual PTRs must be fixed.
- Telstra must be able to detect multiple TRs with FM/FB data. If it can not do this then it will be unable to implement a predictive maintenance scheme. It was shown that when β equals 2, 3 and 4 the mean TR system time was reduced at predictive

powers of 82%, 49% and 37% respectively. Therefore significant performance improvements can be made if Telstra could target its maintenance to those FM/FBs that predict the most TRs.

- Telstra must be aware of the sensitivity of the performance measures to variations in predictive power. As predictive power can only be calculated as a mean value Telstra must take great care that any variations do not result in significant decreases in performance.

6.2 Experiment 2: System performance when PTRs are cleared with the FM/FBs that predict them

This experiment differs from the first in that we do clear PTRs that are in the queue when the FM/FBs that predict them are fixed. This is equivalent to Telstra being able to identify which TRs have been predicted by which FM/FBs. Therefore when Telstra sends a worker to fix a FM/FB, that worker is able to clear the TRs that are related to it.

From the results in section 6.1 we expect that this experiment will reduce maintenance workload (as PTRs do not have to be individually fixed) and it should also reduce mean TR system time as PTRs will not have to wait until they are at the front of the queue to be fixed. Clearing PTRs with the FM/FBs that predict them will result in much shorter queues, which means that FM/FBs will be fixed sooner and fewer PTRs will arrive. However, we do not know how many PTRs can be prevented or to what extent mean TR system time will be reduced.

Diagrammatically the model is still identical to the one in Figure 5.3, however we have changed the way faults are cleared from the queue. Now when a FM/FB is sent to a field worker, all PTRs in the queue that were predicted by that FM/FB are cleared when that FM/FB is fixed. In the case when TRs have priority, PTRs may be fixed before the FM/FBs that predict them. In this case we decided that when a PTR is fixed, the FM/FB that predicted it is cleared from the system. However any other PTRs that were predicted by that FM/FB aren't cleared with the first PTR, they remain in the system and have to be individually cleared. This is consistent with current practises when no FM/FB data is used and all TRs are individually cleared.

6.2.1 Reducing TR volume

The performance measures used in experiment one are also used in this experiment. Therefore, we firstly look at the predictive power required to reduce TR volume. This can be seen in Figure 6.8.

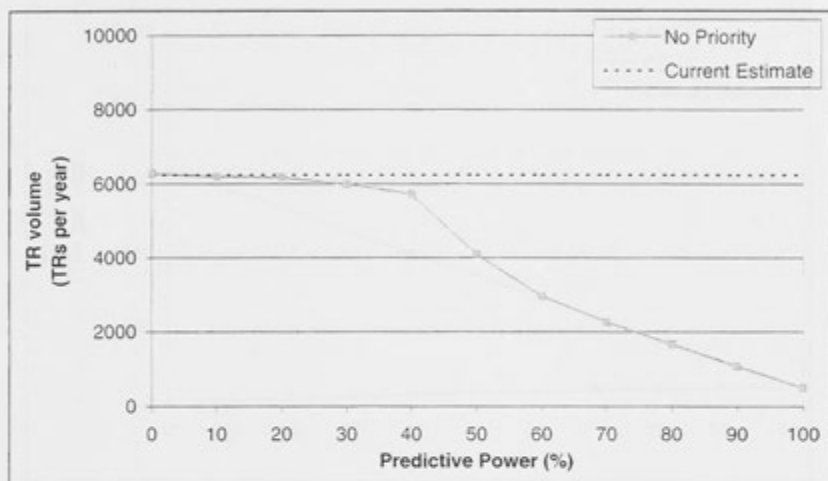


Figure 6.8: Predictive power required to reduce TR Volume when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the number of TRs received per year. A No Priority maintenance scheme is used and β equals 2.

Comparing Figure 6.8 with Figure 6.1 it can be seen that in the first experiment the TR volume did not significantly change until a predictive power of 60%. However, matching FM/FBs with the PTRs they predict results in the TR volume significantly changing at a predictive power of 40%. This is because matching FM/FBs with the PTRs they predict effectively reduces the number of faults that need to be cleared. As a result the queue is shorter and more FM/FB faults are fixed sooner which means fewer PTRs arrive. It can be seen that if Telstra was operating a No Priority scheme with a predictive power of 60% and β equal to 2 it could reduce its TR volume by 48% just by having the ability to identify the TRs that are predicted by each FM/FB.

An interesting observation when clearing PTRs with the FM/FBs that predict them occurs when a FM/FB Priority scheme is used. Figure 6.9 shows the TR volume and PTR volume for each predictive power when a FM/FB Priority scheme is used and β equals 2.

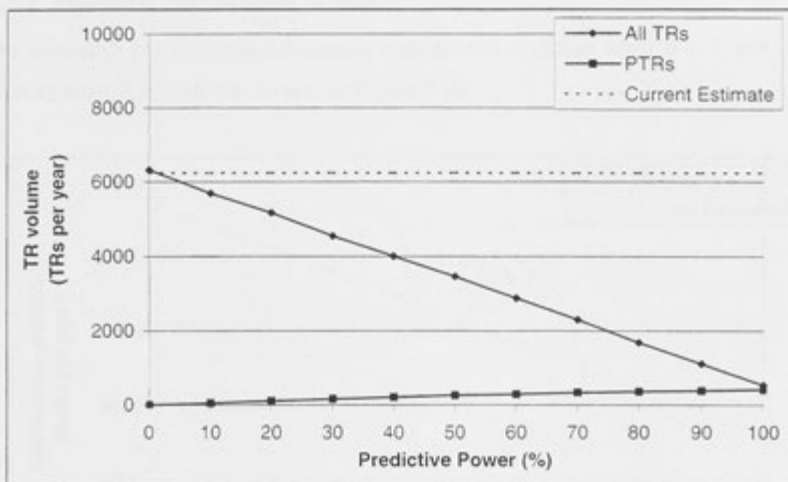


Figure 6.9: Predictive power required to reduce TR Volume when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the number of TRs received per year. A FM/FB Priority scheme is used and β equals 2.

It can be seen in Figure 6.9 that the All TRs curve for a FM/FB Priority scheme is approximately linear. When a FM/FB Priority scheme is used FM/FBs are fixed first and most of the PTRs never arrive. However there is a small number of PTRs that will always arrive which is also plotted in Figure 6.9. It can be seen that the PTR volume curve rises approximately linearly as predictive power increases. This is because there is always a constant percentage of PTRs that arrive before FM/FBs are fixed. As the predictive power increases, so too does the number of PTRs generated and hence so too does the number of PTRs that arrive before the FM/FBs are fixed. It can be seen that when predictive power is 100% approximately 410 PTRs arrive per year. This corresponds to approximately 6.5% of all PTRs. This percentage will vary for different distributions of the delay between a FM/FB arrival and the arrival of the PTRs it predicts. This is significant as it demonstrates that when using a FM/FB Priority scheme

there will always be a percentage of PTRs that can be predicted, but not prevented. Therefore, if Telstra uses a predictive maintenance scheme to reduce the number of TRs it receives each year it must be aware that there will always be a percentage of TRs that can be predicted, but not prevented.

6.2.2 Reducing maintenance workload

The predictive power required to reduce maintenance workload when β is 2, and a No Priority scheme is used, can be seen in Figure 6.10.

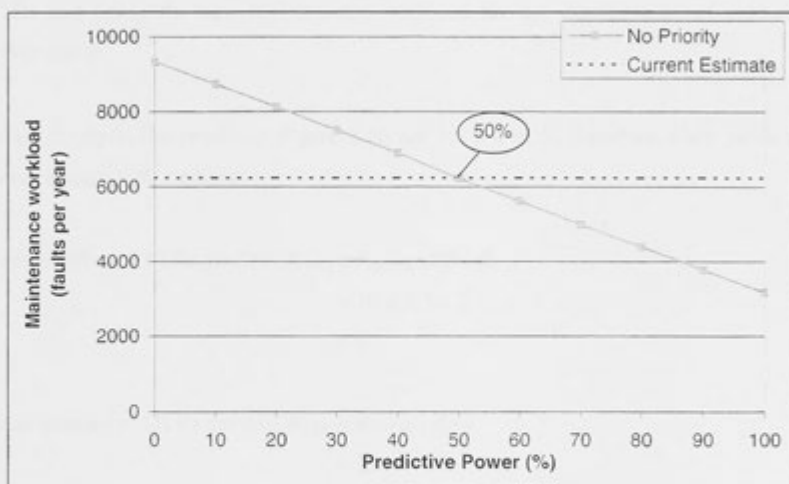


Figure 6.10: Predictive power required to reduce maintenance workload when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the number of faults to be fixed per year. A No Priority scheme is used and β equals 2.

Comparing Figure 6.10 with Figure 6.2 a significant change can be observed. The most striking feature of Figure 6.10 is the linear behaviour of the new maintenance workload curve. In experiment one the maintenance workload consisted of three types of faults: FM/FBs, UTRs, and PTRs. However, when clearing PTRs with the FM/FB that predicts them, maintenance workload consists of only FM/FBs and UTRs. The PTRs predicted by FM/FBs are cleared when the FM/FB is cleared and therefore are not included in the

maintenance workload. Equations (5.2) and (5.3) are used to calculate the mean number of UTRs and mean number of PTRs that arrive per day. They are repeated again below.

$$\#_{UTR} = \#_{TOTAL} - \#_{PTR} \quad (5.2)$$

$$\#_{PTR} = \#_{FM/FB} \cdot PP \cdot \beta \quad (5.3)$$

Recalling from Table 6.1 that without predictive maintenance the initial number of TRs is 20 per day and the number of FM/FBs is 10 per day, we can calculate the number of UTRs and hence the new maintenance workload for any combination of predictive power and β .

As an example, the results in Figure 6.10 are for a β of 2, therefore when predictive power equals 30% we have,

$$\begin{aligned} \text{Mean number of PTRs per day, } \#_{PTR} &= \#_{FM/FB} \cdot PP \cdot \beta \\ &= 10 \times 0.3 \times 2 \\ &= 6 \end{aligned}$$

$$\begin{aligned} \text{Mean number of UTRs per day, } \#_{UTR} &= \#_{TOTAL} - \#_{PTR} \\ &= 20 - 6 \\ &= 14. \end{aligned}$$

Therefore, over a year (6 days a week, 52 weeks of the year) there are 3120 FM/FBs and 4368 UTRs and the new maintenance workload is approximately 7488 faults per year. It can be seen in Figure 6.10 that this is correct.

When clearing PTRs from the queue with the FM/FB that predicts them, which is the case with the FM/FB Priority and No Priority schemes, the predictive power required to reduce maintenance workload can be calculated for any given β . As the current estimate of maintenance workload is equal to $\#_{TOTAL}$ (the TR volume) we can write for each maintenance workload:

Current estimate = FM/FB or No Priority scheme

$$\begin{aligned} \#_{TOTAL} &= \#_{FM/FB} + \#_{UTR} \\ &= \#_{FM/FB} + (\#_{TOTAL} \cdot \#_{PTR}) \\ &= \#_{FM/FB} + (\#_{TOTAL} - \#_{FM/FB} \cdot PP \cdot \beta) \end{aligned}$$

$$\#_{FM/FB} \cdot PP \cdot \beta = \#_{FM/FB}$$

Therefore,

$$PP = \frac{1}{\beta} \quad (6.1)$$

Using equation (6.1) we can calculate that for β equal to 2, 3 and 4 the predictive power required to reduce the maintenance workload is 50%, 33% and 25%. This result is intuitively correct. For example when β equals 4, all jobs can be cleared by fixing 25% of the original load. Therefore to maintain the original workload, 75% of false alarms must be added. It can be seen in Figure 6.11 that simulation results support these calculations.

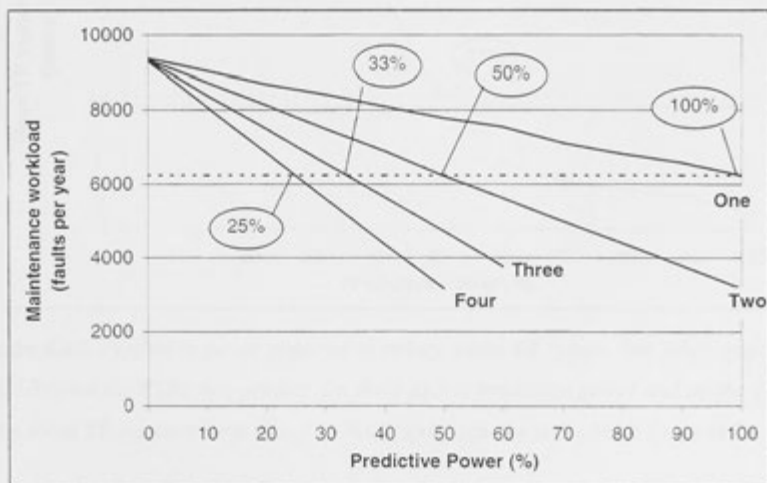


Figure 6.11: Predictive power required to reduce maintenance workload for different β when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the maintenance workload in faults per year. A No Priority scheme is used and each curve has been labeled with its β value.

The significance of this is that for a FM/FB or No Priority scheme maintenance workload is no longer an unknown quantity obtainable only through simulation. If Telstra is able to identify which TRs are predicted by which FM/FBs it will be able to directly calculate the mean maintenance workload for any given predictive power and β . This is not the case when a TR Priority scheme is used. This case will be discussed in section 6.2.5.

6.2.3 Reducing mean TR system time

The minimum predictive power required to reduce mean TR system time when matching FM/FBs with the PTRs they predict can be seen in Figure 6.12. The log scale on the y-axis should be noted.

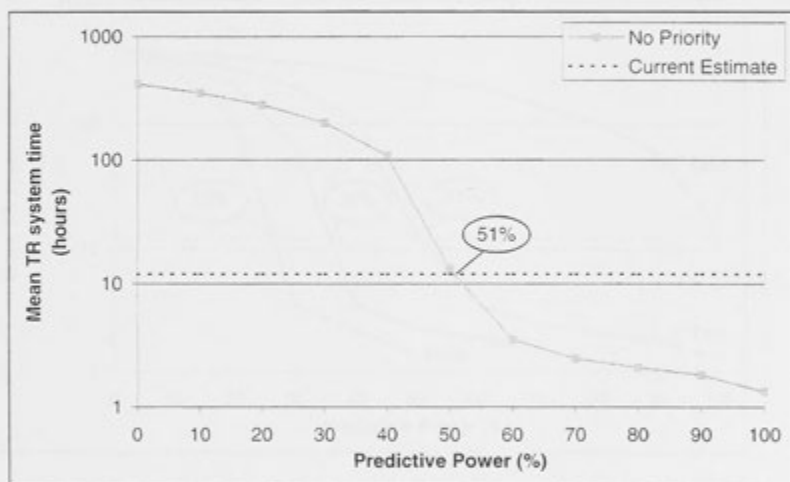


Figure 6.12: Predictive power required to reduce mean TR system time when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the mean TR system time in hours. A No Priority scheme is used and β equals 2.

In experiment one the required predictive power to reduce mean TR system time was 82%. It can be seen in Figure 6.12 that matching FM/FBs with the PTRs they predict reduces the required predictive power to 51%. This drop is a result of two factors. Firstly PTRs are fixed sooner as they are cleared when the FM/FB that predicts them is cleared. Secondly, as PTRs are cleared with the FM/FBs that predict them, the queue is

shorter and any UTRs in the queue are also fixed sooner. Again this result demonstrates how important it is that Telstra is able to identify which TRs are predicted by which FM/FBs.

6.2.4 The effect of varying β

We have already seen that matching FM/FBs with the PTRs they predict allows the minimum predictive power to be calculated using equation (6.1). Therefore, we will now investigate the effect that varying β has on the mean TR system time. The predictive power required to reduce mean TR system time for different β can be seen in Figure 6.13. The log scale on the y-axis should be noted.

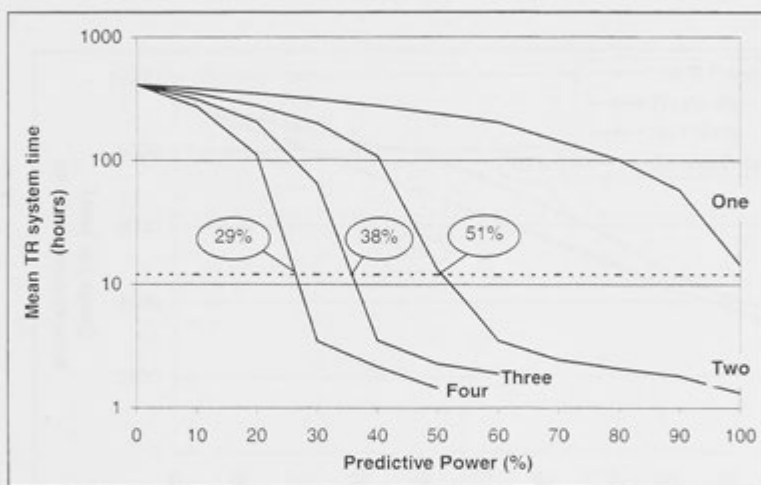


Figure 6.13: Predictive power required to reduce mean TR system time for different β when FM/FBs are matched with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the mean TR system time in hours. A No Priority scheme is used and each curve has been labeled with its β value.

Comparing Figure 6.13 with its experiment one equivalent, Figure 6.4, several important observations can be made. Firstly when matching FM/FBs with the PTRs they predict the mean TR system time is still not reduced when β equals 1. When β equals 2, 3 and 4 the respective minimum predictive powers are reduced from 81%, 46%, and 34% in experiment one to 51%, 38% and 29%. Therefore it can be seen that

matching FM/FB with the PTRs they predict results in a larger benefit when β equals 2 than when β equals 4. This is an important result. If Telstra is able to predict a mean of 4 TRs per correct FM/FB then it is not as important if Telstra is unable to identify which TRs are related to which FM/FBs. On the other hand if Telstra is only able to predict a mean of 2 TRs per correct FM/FB then it is very important that it can identify which TRs are related to each FM/FB.

6.2.5 Different maintenance priority schemes

The effect that different maintenance priority schemes have on the maintenance workload when FM/FBs are matched with the PTRs they predict can be seen in Figure 6.14.

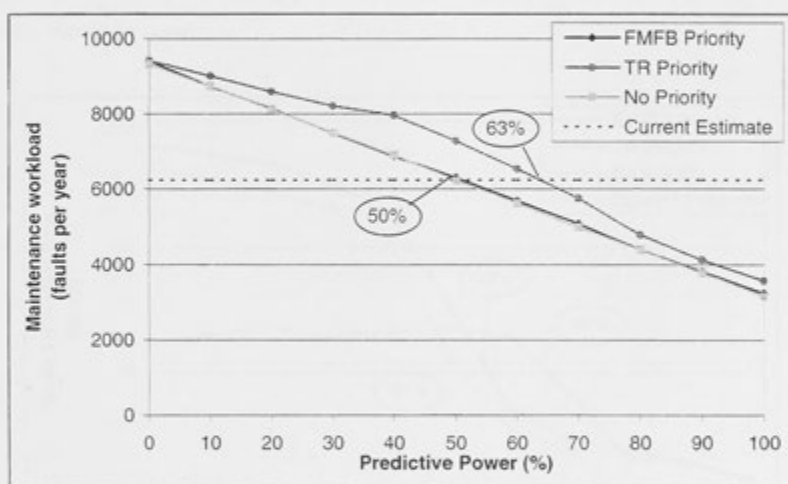


Figure 6.14: Predictive power required to reduce maintenance workload for each maintenance priority scheme when matching FM/FBs with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the number of faults to be fixed per year. The priority schemes are given in the legend and β equals 2.

It can be seen that, when matching FM/FBs with the PTRs they predict, the maintenance workload for the FM/FB and No Priority schemes is the same. This is because in both schemes FM/FBs are fixed before PTRs and maintenance workload consists of only UTRs and FM/FBs.

However when TRs have priority PTRs are often fixed before the FM/FBs that predict them. When this happens the FM/FB is fixed with the first PTR, however any other PTRs predicted by that FM/FB are not cleared. This assumption is consistent with the current practice within many telecommunications maintenance systems. Often TRs that are related by a common cause are not cleared when one of the TRs is fixed. This is can be one of the advantages of using FM/FB data. As a result the workload when a TR Priority scheme is used consists of UTRs, PTRs, false alarm FM/FBs, and correct FM/FBs whose PTRs have not yet arrived.

How different maintenance priority schemes affect mean TR system time when FM/FBs are matched with the PTRs they predict can be seen in Figure 6.15. The log scale on the y-axis should be noted.

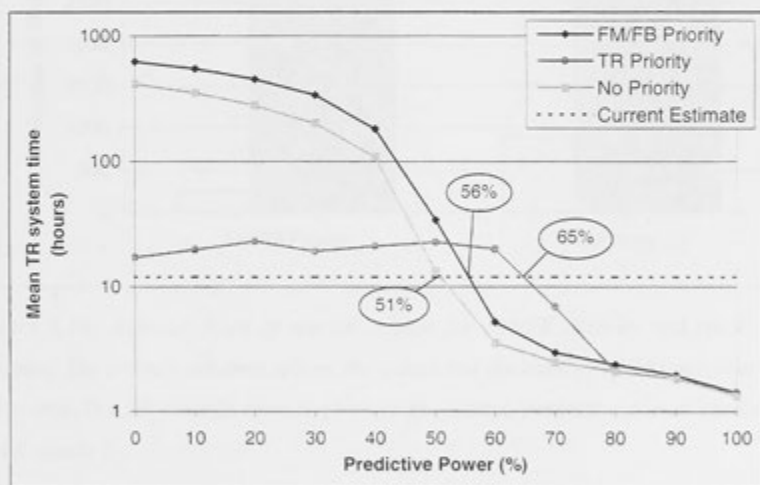


Figure 6.15: Predictive power required to reduce mean TR system time for each maintenance priority scheme when FM/FBs are matched with the PTRs they predict. On the x-axis is predictive power and on the y-axis is the mean TR system time in hours. The priority schemes are shown in the legend and β equals 2.

By comparing Figure 6.15 with Figure 6.6 we can see there are significant differences that result from matching FM/FBs with the PTRs they predict. In experiment one

FM/FB Priority required the lowest predictive power of 58%. In this experiment the required predictive power for FM/FB Priority dropped slightly to 56%. However, a No Priority scheme requires the lowest predictive power of 51%, down from 82% in experiment one. To understand why No Priority performs better than FM/FB Priority we need to study the PTRs and UTRs separately.

At a predictive power of 50% the TR volume is lower for FM/FB Priority than No Priority as there are fewer PTRs arriving. This can be seen in Figure 6.16.

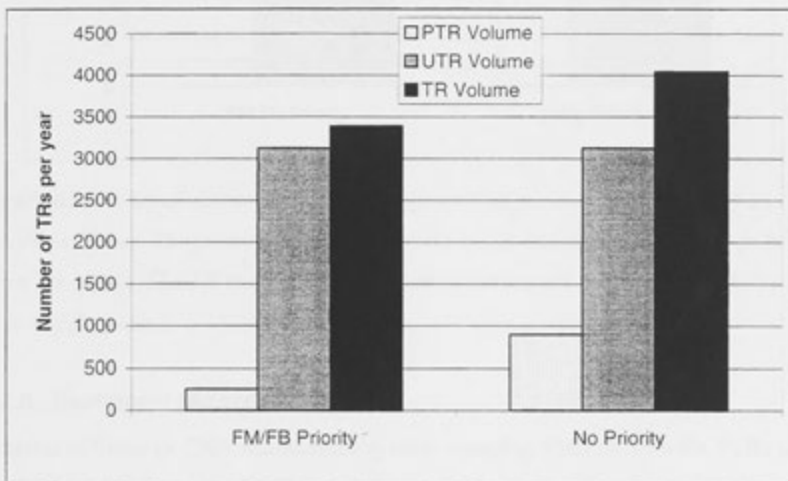


Figure 6.16: A break down of the TR volume for FM/FB Priority and No Priority schemes. The priority schemes are on the x-axis and the number of TRs per year is on the y-axis. The TR classification is given in the legend, predictive power equals 50% and β equals 2.

As TR volume consists of mostly UTRs, the mean UTR system time will have a significant impact on mean TR system time. The mean PTR system time will be kept relatively small as PTRs are cleared when the FM/FB that predicts them is cleared. In a FM/FB Priority scheme UTRs must wait longer than any other scheme as they do not have priority and are not fixed on a FIFO basis. This is the reason why FM/FB Priority has a higher mean TR system time than No Priority, even though there are less TRs in the system. This can be seen in Figure 6.17.

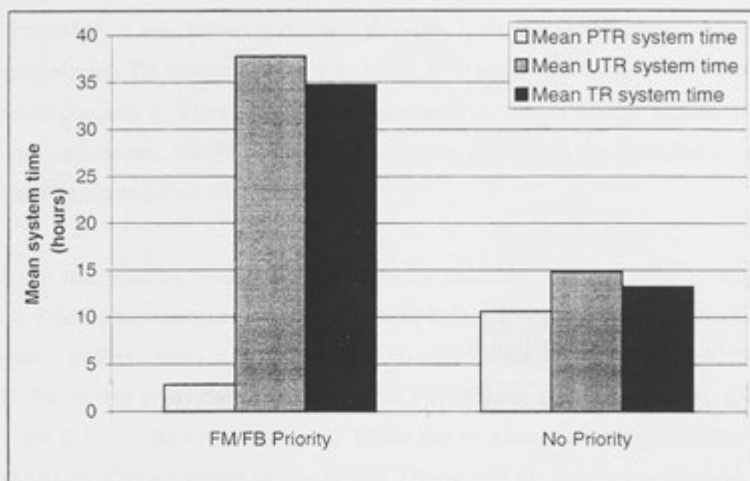


Figure 6.17: A break down of the mean TR system time for the FM/FB Priority and No Priority schemes. The priority schemes are on the x-axis and mean system time in hours is on the y-axis. The TR classification is given in the legend, predictive power equals 50% and β equals 2.

6.2.6 Experiment two conclusions

In terms of Telstra's CAN maintenance system, matching FM/FBs with the PTRs they predict is the same as having the ability to identify which TRs are related to which FM/FBs. Therefore when a worker fixes a FM/FB they can also clear any related TRs from the queue. The results from experiment two suggest that significant performance improvements can be made by having this ability. These performance improvements and their implications are summarised below:

- When β equals 2 and a No Priority scheme is used, TR volume begins to significantly reduce at a predictive power of 40% compared to 60% in experiment 1. If Telstra is operating a No Priority scheme with a predictive power of 60% and β equal to 2 it can reduce its TR volume by 48% just by having the ability to identify the TRs that are related to each FM/FB.

- As β increases the importance of identifying which TRs relate to which FM/FBs diminishes. It was shown that when β equals 2, the predictive power required to reduce mean TR system time is reduced by 37% as opposed to a reduction of 21% when β equals 4. Therefore if Telstra is unable to predict a large number of TRs with each correct FM/FB, the ability to identify which TRs are predicted by which FM/FBs becomes more important.
- Mean maintenance workload can be directly calculated when FM/FB Priority and No Priority are used. As FM/FBs are fixed before PTRs the ability to clear PTRs with FM/FBs means that maintenance workload consists of only FM/FBs and UTRs. In this study the mean number of FM/FBs per day is a constant, given in Table 6.1, and the mean number of UTRs can be calculated using equations (5.2) and (5.3). The advantage of this is that Telstra will be able to calculate its mean daily workload⁴ in advance and can use this for scheduling field staff.
- When matching FM/FBs with the PTRs they predict the minimum predictive power required to reduce maintenance workload was found to be $(\beta)^{-1}$ for FM/FB Priority and No Priority. If Telstra is able to determine the β of its FM/FB data it will be able to quickly determine the minimum predictive power required to reduce maintenance workload. If Telstra had a TR Priority scheme, or if it could not identify which TRs are related to which FM/FBs, it would need simulation to determine this value.
- It can be seen in Figure 6.18 that No Priority is the scheme that reduces the performance measures with the lowest predictive power of 51%. Therefore if Telstra could identify the TRs that are related to each FM/FB it would not need any maintenance priority scheme at all. The best performance is obtained when faults are fixed on a FIFO basis.

⁴ Only valid for FM/FB Priority or No Priority.

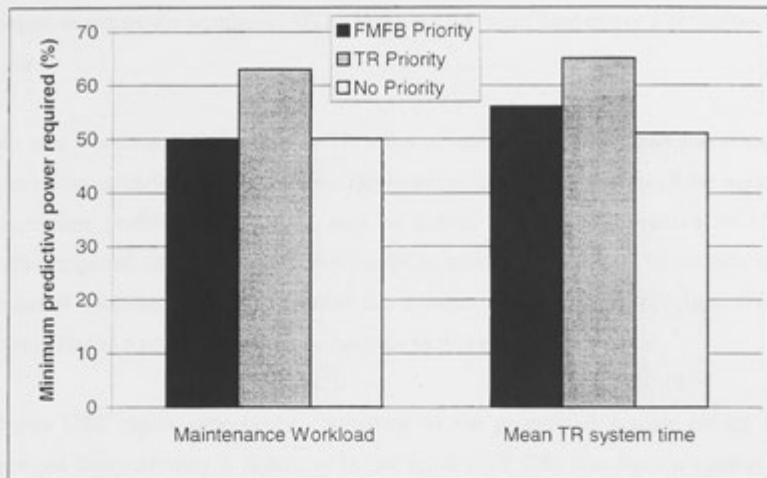


Figure 6.18: The minimum predictive power required to reduce maintenance workload and mean TR system time when β equals 2. On the x-axis is each performance measure and on the y-axis is the minimum predictive power that reduces the performance measure below the estimate of its current performance. The priority schemes are given in the legend.

It was shown that even though a FM/FB Priority scheme results in fewer TRs, it has a higher mean TR system time as UTRs must wait longer to be fixed. The implication is that a priority scheme is required that gives UTRs priority when their system time is going to exceed a predefined value. Such a scheme is the Estimated Time to Fix (ETF) Priority scheme and its performance is examined in experiment three.

6.3 Experiment 3: Analysis of Estimated Time to Fix (ETF) Priority scheme

Experiment three: Analysis of Estimated Time to Fix (ETF) Priority scheme, is the same as experiment two except it aims to improve system performance through the use of an ETF Priority scheme. This scheme was introduced in section 5.6.1.

This experiment is motivated by results from experiment two which show that even when mean TR system time is relatively small, there is a large number of TRs (predominantly UTRs) that have high system times. By using an ETF Priority scheme it

is hoped to reduce the number of UTRs that have a system time above a predefined cut-off time.

Until now we have considered only TR volume, maintenance workload and mean TR system time as performance measures. However, as shown in Figure 6.17 the mean TR system time performance measure may be hiding the poor performance of UTRs. Another measure of considerable importance to telecommunications companies is the number of TRs that have a system time that exceed a predefined cut-off time. We will be using this as a fourth performance measure in this experiment.

Telstra's CSG repair time is the equivalent of the predefined system cut-off time. Therefore demonstrating a reduction in the number of TRs that have a system time greater than a predefined cut-off is the same as reducing the number of times Telstra misses a CSG repair time. Telstra is legally bound under its CSG to fix a customer reported fault within a specified time. If this time is exceeded then the affected customer is entitled to compensation. Gilchrist [6] reports that Telstra's annual CSG compensation bill could be as high as \$70 million in 2000.

6.3.1 Reducing TR volume

In the first part of this experiment we arbitrarily set the ETF cut-off time to 16 hours and examine system performance. In section 6.3.5 the sensitivity of performance to variations in this cut-off time is investigated. However, to begin our analysis we look at the TR volume for each priority scheme. This can be seen in Figure 6.19.

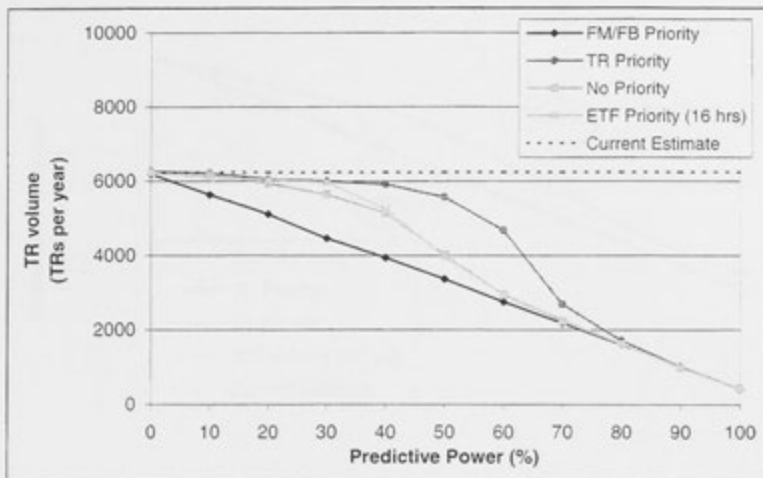


Figure 6.19: Predictive power required to reduce TR volume. Predictive power is on the x-axis and the number of TRs received per year is on the y-axis. The priority schemes are shown in the legend and β equals 2.

It can be seen in Figure 6.19 that the ETF Priority scheme performs similar to the TR Priority scheme for predictive powers between 0% and 30% and similar to the No Priority scheme for predictive powers between 40% and 100%. This is because at predictive powers between 0% and 30% the UTR volume is high and the workload is high. This means there are many UTRs that are going to miss the cut-off time and the ETF Priority scheme operates similar to the TR Priority scheme. However, as predictive power increases there are fewer UTRs and also fewer faults as more FM/FBs are preventing PTRs. This means there are less UTRs that are going to miss the cut-off and the ETF Priority scheme operates more like a No Priority maintenance scheme.

6.3.2 Reducing maintenance workload

Maintenance workload for the ETF Priority scheme is the same as that for the FM/FB and No Priority schemes as the ETF Priority scheme doesn't prioritise PTRs. This means that all PTRs are cleared with the FM/FBs that predict them and the maintenance workload consists of FM/FBs and UTRs. This can be seen in Figure 6.20.

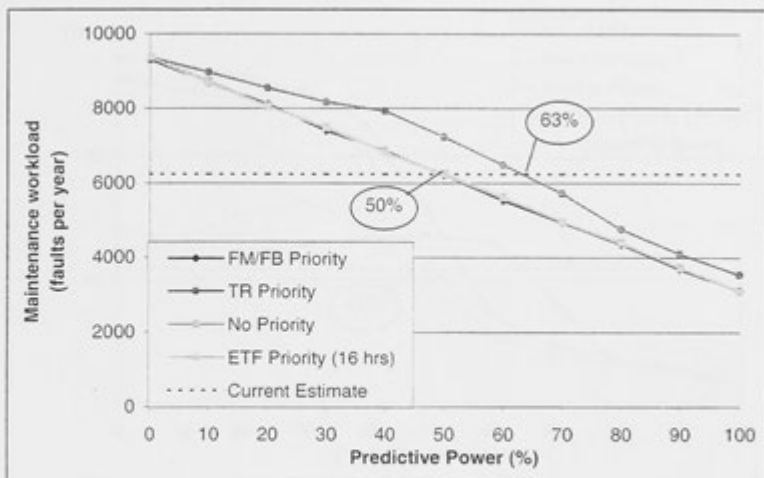


Figure 6.20: Predictive power required to reduce maintenance workload. Predictive power is on the x-axis and the number of faults received is on the y-axis. The priority schemes are shown in the legend and β equals 2.

6.3.3 Reducing mean TR system time

The third performance measure is the mean TR system time. The results are shown in Figure 6.21. The log scale on the y-axis should be noted.

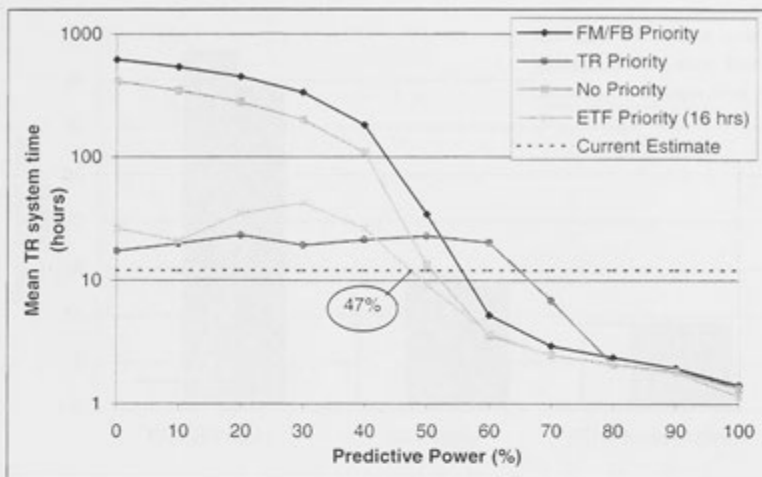


Figure 6.21: Predictive power required to reduce mean TR system time. Predictive power is on the x-axis and the mean TR system time in hours is on the y-axis. The priority schemes are shown in the legend and β equals 2.

It can be seen that the ETF Priority scheme with a cut off of 16 hours reduces mean TR system time below the current estimate at the lowest predictive power of 47%. It can be seen that for predictive powers greater than 60% the ETF Priority scheme is almost identical to the No Priority scheme. Again this is because there are fewer UTRs failing to make the cut-off and the ETF Priority scheme operates the same as the No Priority scheme. For predictive powers below approximately 42% a TR Priority scheme performs the best as all TRs are given priority.

Figure 6.22 shows an analysis of the mean TR system time when predictive power is 50% and β equals 2. It can be seen that the ETF Priority scheme lowers the mean UTR system time, which helps to reduce the mean TR system time. This demonstrates that the ETF Priority scheme is able to rectify the problem encountered in experiment two when the mean UTR system time was much higher than the mean PTR system time.

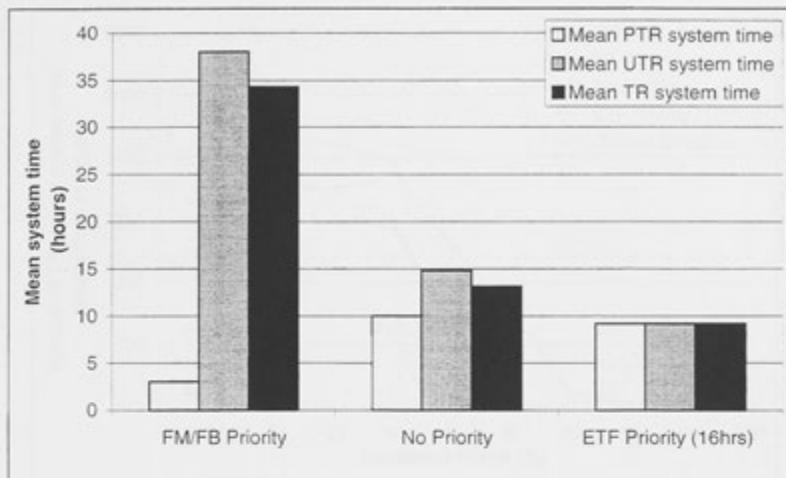


Figure 6.22: A break down of the mean TR system time for the FM/FB Priority, No Priority and ETF Priority schemes. The priority schemes are on the x-axis and mean system time in hours is on the y-axis. The TR classification is given in the legend, predictive power equals 50% and β equals 2.

6.3.4 Reduce the number of TRs that have a system time greater than a predefined time.

One of the motivations for the introduction of the ETF Priority scheme was to reduce the number of TRs that have a system time greater than a predefined time. The results when counting the number of TRs that have a system time greater than 16 hours can be seen in Figure 6.23.

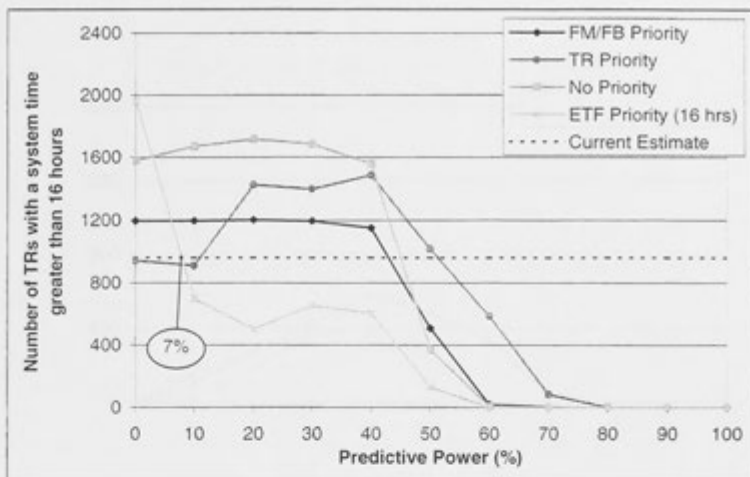


Figure 6.23: Number of TRs that have a system time greater than 16 hours. Predictive power is on the x-axis and the number of TRs that have a system time greater than 16 hours is on the y-axis. The priority schemes are shown in the legend and β equals 2.

It can be seen in Figure 6.23 that the ETF Priority scheme is the best performing scheme for predictive powers between 7% and 60%. Initially, at a predictive power of 0%, the number of TRs that miss a 16 hour cut-off for the ETF Priority scheme is the highest at approximately 1900. This number then falls to around 500 at a predictive power of 20% before it begins to rise again at a predictive power of 30%. The rising and falling of the number of TRs that miss a 16 hour cut-off is due to the combination of PTR and UTR faults which can be seen in Figure 6.24 and Figure 6.25.

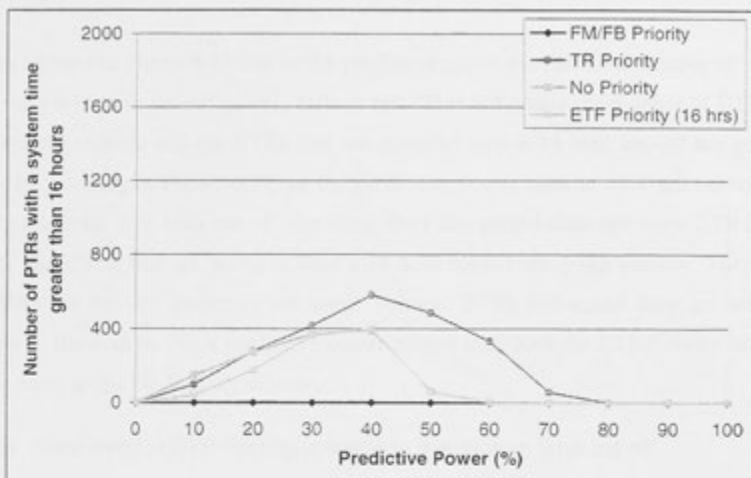


Figure 6.24: Number of PTRs that have a system time greater than 16 hours. Predictive power is on the x-axis and the number of PTRs that have a system time greater than 16 hours is on the y-axis. The priority schemes are shown in the legend and β equals 2.

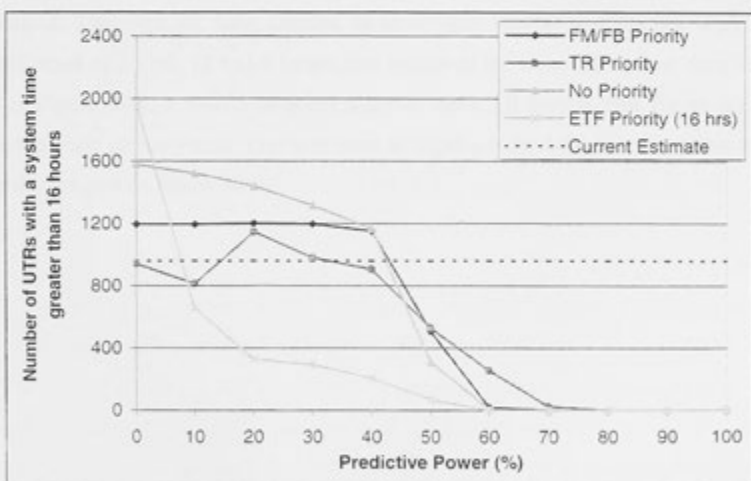


Figure 6.25: Number of UTRs that have a system time greater than 16 hours. The predictive power is on the x-axis and the number of UTRs that have a system time greater than 16 hours is on the y-axis. The priority schemes are shown in the legend and β equals 2.

It can be seen in Figure 6.25 that as the predictive power increases the number of UTRs that miss a 16 hour cut-off quickly falls to zero. This is because the number of UTRs in the system reduces and the UTRs that are going to miss a 16 hour cut-off are getting priority. Looking at Figure 6.24, as the predictive power rises to 40% the number of PTRs that miss a 16 hour cut-off also rises. Over this period there are more UTRs than PTRs and UTRs that are going to miss a 16 hour cut-off are given priority. Therefore FM/FBs are waiting longer in the queue so more PTRs arrive and they are waiting longer in the system. For a predictive power greater than 30% the ETF Priority scheme is the same as the No Priority scheme.

6.3.5 Sensitivity of ETF Priority scheme to the system time cut-off

In the ETF Priority results presented so far a UTR system time cut-off of 16 hours has been used. In this section we will investigate the effect of variations in this time. As the cut-off for UTR system time increases fewer UTRs will miss the cut-off and the ETF Priority scheme will act predominantly the same as the No Priority scheme. However as the cut-off is reduced more UTRs will miss the cut-off time and more UTRs will be prioritised. Therefore we have decided to investigate system performance with UTR cut-off times of 20, 16, 12 and 8 hours. The results of the mean TR system time can be seen in Figure 6.26. It should be noted that this mean TR system time figure does not use a log-scale on the y-axis. This was done to highlight the differences in performance at predictive powers below 40%.

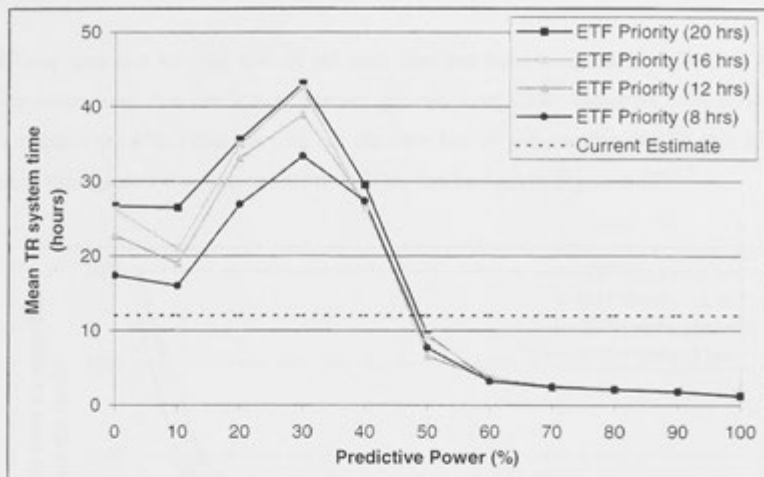


Figure 6.26: Sensitivity of mean TR system time to variations in UTR system time cut-off. On the x-axis is the predictive power and on the y-axis is mean TR system time in hours. β equals 2 and the cut-off times of each ETF Priority scheme are given in the legend.

From Figure 6.26 it can be seen that at predictive powers of 40% or greater the UTR system time cut-off does not really effect mean TR system time. However for predictive powers below 40% it can be seen that an 8 hour cut-off results in the lowest mean TR system times even though these mean TR system times are greater than the current estimate.

If Telstra implemented an ETF Priority scheme it could not operate with a predictive power less than 50% as this is the minimum predictive power that reduces maintenance workload. It can be seen that at predictive powers of 50% and greater the cut-off time chosen does not significantly effect the mean TR system time. It can also be seen that the minimum predictive power that reduces maintenance workload is approximately the same for each cut-off time. The implication of this is that Telstra could use a small cut-off time in their CSG to help distinguish themselves from their competitors. For example if Telstra guarantee customers that any reported faults will be fixed within 8 hours and a competitor guarantees to fix faults within 16 hours Telstra have a distinct sales advantage.

We have seen that varying the cut-off time does not have a significant effect on mean TR system time for predictive powers greater than 40%. However, we have not investigated the effect that varying cut-off time has on the number of TRs that have a system time greater than the cut-off time. This can be seen in Figure 6.27.

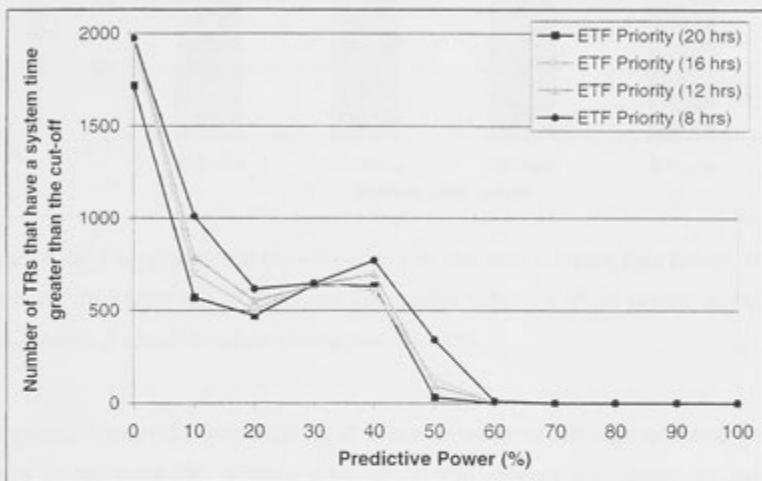


Figure 6.27: The sensitivity of the number of TRs with a system time greater than the cut-off to variations in cut-off time. On the x-axis is the predictive power and on the y-axis is the number of TRs with a system time greater than the cut-off. β equals 2 and the cut-off times of each ETF Priority scheme are given in the legend

In Figure 6.27 it can be seen that when predictive power is below 60% a system time cut-off of 8 hours results in the most TRs missing a system time cut-off. At predictive powers of 60% or more, all system cut-off times result in the same number of TRs that miss a cut-off, approximately zero. At a predictive power of 50%, an 8 hour system time cut-off results in the most TRs missing a cut-off. However, Figure 6.27 does not tell us by what percentage the current estimate has been reduced. Figure 6.28 shows the percentage by which the current estimate is reduced when predictive power is 50% and β equals 2.

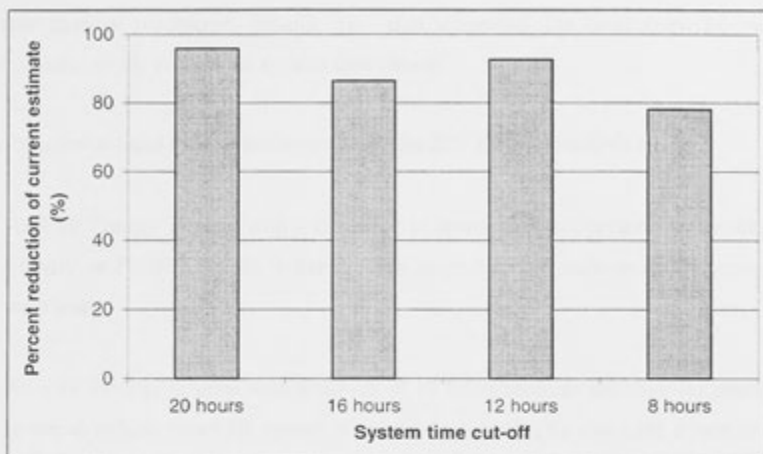


Figure 6.28: The reduction in the number of TRs that miss a system time cut-off. On the x-axis are the system cut-off times and the percent reduction of the current estimate is on the y-axis. β equals 2 and predictive power is 50%.

Comparing Figure 6.28 with Figure 6.27 it can be seen that although an 8 hour cut-off results in the most TRs missing a cut-off, it still reduces the current estimate by approximately 78%. It can be seen that a 20 hour system time cut-off reduces the current estimate by approximately 96%. However most customers would not be happy with a CSG of 20 hours.

If Telstra's predictive power was 50% it would have to make a decision regarding the operating scheme it should use. It could set its system time cut-off to 20 hours and it would reduce its number of missed CSG repair times by approximately 96%. However it may lose many of its customers as they may not accept a CSG repair time of 20 hours. On the other hand, if Telstra set its cut-off to 8 hours it could still reduce its number of missed CSG repair times by 78% and its new CSG repair time would make it much more attractive to potential customers.

6.3.6 Experiment three conclusions

In this section we have looked at the ETF Priority scheme and how it can be used to reduce mean TR system time as well as the number of TRs that have a system time

greater than a predefined cut-off. We also examined the sensitivity of system performance to the predefined system time cut-off.

The conclusions and recommendations from the ETF Priority analysis are:

- An ETF Priority scheme with a cut-off of 16 hours does not perform better than No Priority or FM/FB Priority schemes with respect to TR volume and maintenance workload.
- An ETF Priority scheme with a cut-off of 16 hours requires the smallest predictive power to reduce mean TR system time and number of TRs that have a system time greater than the cut-off. The minimum predictive power required is 47% and 7% respectively. However Telstra would not be able to operate with such low predictive powers because it can be seen in Figure 6.29 that the minimum predictive power that reduces maintenance workload is 50%. Looking at a predictive power of 50% the ETF Priority scheme is able to reduce the current performance of mean TR system time and number of TRs that have a system time greater than the cut-off by 24% and 87% respectively.
- If we equate the number of TRs that miss a 16 hour cut-off to the number of times Telstra violate a CSG then according to Gilchrist [6] an 87% reduction in Telstra's 2000 CSG compensation bill would save it approximately \$60 million in 2000.
- It was shown that at predictive powers below 40%, mean TR system time increased by approximately 10 hours when the system time cut-off was varied between 8 hours and 20 hours. However, for predictive powers greater than 50% the mean TR system time was not sensitive to the system cut-off times we investigated. This means that if Telstra could operate a predictive maintenance scheme with predictive powers greater than 50% it would be able to advertise small CSG repair times to attract customers.
- When predictive power is 50% an 8 hour cut-off time reduces the current estimate of the number of TRs that miss a cut-off by 78%. A 20 hour cut-off reduces the current estimate by 96%. This means that if Telstra's predictive power was 50% it would

need to decide between attracting customers with a small CSG repair time or further reducing its CSG compensation bill, but potentially losing customers, by having a large CSG repair time of 20 hours. For predictive powers of 60% or more an 8 hour cut-off resulted in zero TRs missing the system time cut-off.

A summary of the predictive powers required to reduce each of the performance measures below their current levels when β equals 2 is shown in Figure 6.29.

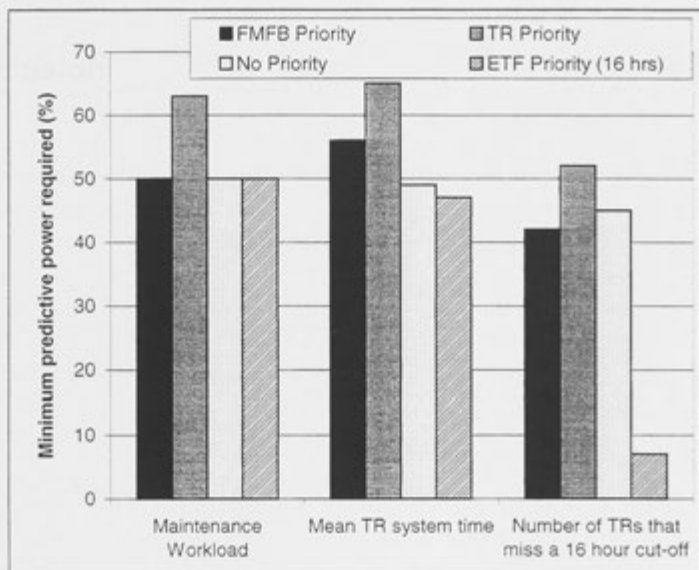


Figure 6.29: The minimum predictive power required to reduce each performance measure when β equals 2. On the x-axis is each performance measure and on the y-axis is the minimum predictive power that reduces the performance measure below the estimate of its current performance.

Chapter 7

Conclusion

This thesis is motivated by the need to explore more effective ways of maintaining a telecommunications network. Specifically we study a predictive maintenance approach that predicts which network problems customers will report in the future.

7.1 FM/FB data analysis

An analysis of FM/FB data is undertaken to gain a better understanding of how it can be used in a predictive maintenance scheme. The first analysis looks at predictive power and determines the characteristics of lines that are most likely to correctly predict future customer TRs. From the results the predictive power of FM/FB data is surprisingly low. Considering FB lines are disconnected from the network it is especially surprising that their predictive power is as low as 11.8%.

We found that the best method to increase predictive power is to group FB lines that are domestic customers and that are within a 30 o-pair range. Counting each group as a single ticket of work (ToW) results in a predictive power of 50.7%. Unfortunately however, only 1% of Telstra's daily TR volume can be predicted through the use of FB ToWs. At 7% of the daily TR volume, combined FM/FB data has the greatest capability to prevent future TRs. The implication of these results is that if Telstra wish to improve the predictive power of FM/FB data it will reduce the number of TRs it can possibly prevent. On the other hand if it wants to prevent as many TRs as possible it must do so with a reduced predictive power.

From this analysis it became clear that further analysis is required to investigate why so few FB customers report their disconnected lines. It is possible that a reason why so few FB lines are reported is that customers are not actively using them. If this is the case then identifying and testing the lines that are actively used by customers could possibly increase predictive power. Further research could also be conducted into optimal FM and FB insulation resistance settings. Currently these are set by Telstra at 50k Ω and 20k Ω respectively however it is not clear what impact changing these settings would have.

It was shown that 81% of TRs predicted by a FB arrive within 48 hours of first being FB and 42% of TRs predicted by a FM arrive within 48 hours of first being FM. The implication of this result is that if Telstra wish to use FB data to predict future customer

TRs it must react very quickly to FB alarms. In order to react quicker to FB alarms the current practise of obtaining FB data three times per day needs to be changed so that FB data is received as close to real time as possible. FM data allows a longer time to fix a fault before a customer reports it, however FMs also have the worst predictive power.

A possible explanation of why FB lines are not being reported by customers is that lines are not remaining FB, and hence disconnected, for an extended period of time. It is possible that many lines are intermittently appearing and disappearing from FB buffers. To investigate this we analysed a set of FB lines and found that 87.1% of FB lines had been FB in the previous 48 hours and 86.7% of FB lines will be FB again in the next 48 hours. This result suggests that FB lines are relatively stable and do not intermittently appear and disappear from FB status. The implication of this result is that Telstra is able to send a worker to fix a FB fault confident that the FB line will not disappear from FB status. If lines were disappearing from FB status then Telstra would be wasting resources sending workers to fix them.

The analysis into the relationship between the number of times a line is FB and the predictive power found that 30% of lines were FB only once. This directly contradicts the results of section 4.4, which show that only 13% of FB lines should appear only once. Immediately this questions the validity of the data we have used. We are confident that our analysis methods are correct and therefore can only conclude that the FM/FB data that Telstra receive is inconsistent and unreliable. Before Telstra could implement a predictive maintenance scheme based on FM/FB data it would need to conduct further analysis to determine the causes of the inconsistencies we are seeing.

The analysis into the relationship between the number of times a line is FB and the predictive power reveals that lines that appear FB 5 or 6 times have the greatest predictive power of approximately 27%. While this is an interesting observation and it provides a better understanding of the dynamics of FB data it is not practically useful. It was shown in section 4.3 that the longer Telstra wait after observing a FB line, the less chance it has of beating a customer to a fault. Therefore Telstra cannot afford to wait to see if a line is going to be FB six times or twelve times before it decides to fix it.

One obstacle in this analysis is the fact that FM/FB data is currently unreliable. As an AXE exchange can refuse permission to access its FM/FB buffer it is not clear if a line is no longer FM/FB or if it was not accessed from the exchange. Until Telstra is able to reliably obtain FM/FB data from the exchanges this will continue to be a problem.

Another area for further investigation is to determine why lines leave a FM/FB condition. How were they fixed? What caused the change? Will these lines become FB or FM again at a later time?

As the predictive power, and the percentage of the daily TR volume that is predicted by FM/FB data is so small further investigation is required to find other technologies that could be used for predictive maintenance. For example testing the insulation resistance alone may not be the best test to predict future customer TRs. It may be the case that there are other tests that are able to predict future customer TRs more accurately.

7.2 Modelling and simulating Telstra's CAN maintenance system

Telstra's CAN maintenance system is modelled as a stochastic discrete event system. In this model we establish a relationship between FM/FB data and customer TRs that has not previously been understood. Equation (5.5) defines this relationship which enables us to calculate mean UTR inter-arrival time, θ_{UTR} , when given PP , β , $\theta_{FM/FB}$ and μ .

If Telstra is unable to identify which TRs are predicted by which FM/FBs its maintenance workload and mean TR system time will require relatively high minimum predictive powers before they can be reduced below current levels. This is because individual PTRs must be fixed. When β equals 2 a FM/FB Priority scheme reduces all performance measures at the lowest predictive power of 58%. We show that if Telstra is unable to predict at least two TRs per FM/FB it will not be able to successfully implement a predictive maintenance scheme. It was shown that when β equals 2, 3 and 4 the mean TR system time is reduced at predictive powers of 82%, 49% and 37% respectively. Therefore significant performance improvements can be made if Telstra could target its maintenance to those FM/FBs that predict the most TRs.

If Telstra is able to identify which TRs are predicted by which FM/FBs, when β equals 2, a No Priority maintenance scheme is the best performing scheme reducing all

performance measures with a minimum predictive power of 51%. It was found that when β is small it is more important to be able to identify which TRs are predicted by which FM/FBs than when β is large. This is because when β is large there are fewer faults in the queue and more PTRs are prevented from arriving. When β is small the queue is longer and it is more difficult to fix FM/FBs before PTRs arrive. An interesting result is seen at a predictive power of 50% when the FM/FB Priority scheme reduces the TR volume more than the No Priority scheme but its mean TR system time is greater. This is because UTRs have to wait longer in the queue in a FM/FB Priority scheme. To address this problem, and to also try and reduce the number of TRs that have a system time greater than a predefined cut-off an ETF Priority scheme is introduced.

The ETF Priority scheme prioritises UTR faults that are likely to have a system time greater than a predefined cut-off. Simulation using this scheme shows that with a system cut-off time of 16 hours the ETF Priority scheme is able to reduce all performance measures with a minimum predictive power of 50%. In the first two experiments the limiting performance measure (ie the one that requires the greatest predictive power) is the mean TR system time. When using an ETF Priority scheme the limiting measure is the maintenance workload. As the mean maintenance workload can be calculated⁵ from equations (5.2) and (5.3), the minimum predictive power is limited to 50% when β is 2. When predictive power is 50% it was shown that the ETF Priority scheme reduces the number of TRs that miss a 16 hour cut-off by approximately 87%. The implication of this result is that Telstra, or any telecommunications company that has a legal obligation to meet customer service guarantees (CSGs), can greatly reduce their compensation bills by using an ETF Priority scheme. It was found that for predictive powers equal to or greater than 60% system performance is not sensitive to variations in system cut-off time. When predictive power is 50% an 8 hour cut-off time reduces the current estimate of the number of TRs that miss a cut-off by 78%. A 20 hour cut-off reduces the current estimate by 96%. This means that if Telstra's predictive power is 50% it will need to decide between attracting customers with a small CSG repair time, or further reducing its CSG compensation bill and potentially losing customers by having a large CSG repair time.

⁵ When PTRs are cleared with the FM/FBs that predict them

An area of further study for the modelling and simulation of a predictive maintenance scheme is to investigate more advanced operating schemes and more complex models. Currently the model assumes all TRs and FM/FBs are identical in that they all take the same mean time to fix. It also assumes that all workers are identical in that they all have the same skills and fix faults at the same rate. A more accurate model would have different fault types, each fault type having its own mean time to repair. If workers also had different skill levels when fixing different faults then certain faults could be assigned to certain workers.

The results from the simulation analysis can not be compared directly to Telstra's current operation to decide if it could use FM/FB data for predictive maintenance. The reason for this is that Telstra's current system was not accurately modelled in our simulation experiments. For example, Telstra does not know the mean FM/FB inter-arrival time so we have made assumptions in our analysis. However, we have been able to demonstrate the requirements of FM/FB data if Telstra is to use it in a predictive maintenance scheme. It was also shown that simulation is a valuable tool when trying to understand the dynamics of a system as well as the implications of any operating decisions.

References

1. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
2. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
3. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
4. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
5. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
6. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
7. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
8. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
9. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
10. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
11. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
12. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
13. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
14. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
15. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
16. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
17. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
18. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
19. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.
20. Gossman, J. A. *Healthcare in the United States*. New York: Oxford University Press, 2005.

- [1] Bouloutas, A. T., Calo, S., and Finkel, A. "Alarm Correlation and Fault Identification in Communication Networks", IEEE Transactions on Communications, Vol. 42, 1994, p. 523-533.
- [2] Brately, P., Fox, B. L., Schrage, L. E. "A Guide to Simulation", 2nd Edition, Springer-Verlag, 1987.
- [3] Buzacott, J. A., Shanthikumar, J. G., "Stochastic models of manufacturing systems", Prentice Hall, 1993.
- [4] Cassandras C. G., "Discrete Event Systems: Modelling and Performance Analysis", Irwin Publishing, 1993.
- [5] Gardner, Robert D., Harle, David A. "Pattern discovery and specification techniques for Alarm Correlation", NOMS '98, Proceedings of the IEEE Network Operations and Management Symposium, IEEE, New York, NY, USA, Vol. 3, 1998, p. 713-722.
- [6] Gilchrist, M., "Telstra payouts left on hold", The Australian, Thursday December 9, 1999, p. 1.
- [7] Grayson, I., "CA's high-tech clairvoyant", The Australian, Tuesday July 21, 1999, p. 55.
- [8] Guido, B., Roberto, G., Di Tria, P., Bisio, R. "Work Force Management (WFM) Issues", NOMS '98, Proceedings of the IEEE Network Operations and Management Symposium, IEEE, New York, NY, USA, Vol. 2, 1998, p. 473-482.
- [9] Kashmirian, A. S., Robinson, W., "Automatic evaluation of pressurised cable alarms", Telecommunication Journal of Australia, Vol. 42, No. 2, 1992, p. 43-46.

- [10] Katzela, I., Schwartz, M. "Schemes for Fault Identification in Communication Networks", *IEEE Transactions on Networking*, Vol. 3, No. 6, 1995, p. 753-764.
- [11] McIntyre, J. R. "Using Artificial Intelligence and a Graphical Network Database to Improve Service Quality in Telecom Australia's Customer Access Network", *Telecommunication Journal of Australia*, Vol. 42, No. 2, 1992, p. 3-6.
- [12] Meira, D. M., Nogueira, J. M. S. "Modelling a Telecommunication Network for Fault Management Applications", *NOMS '98. Proceedings of the IEEE Network Operations and Management Symposium*, IEEE, New York, NY, USA, Vol. 3, 1998, p. 723-732.
- [13] Montana, D., Bidwell, G., Moore, S. "Using Genetic Algorithms for Complex, Real-Time Scheduling Applications", *NOMS '98. Proceedings of the IEEE Network Operations and Management Symposium*, IEEE, New York, NY, USA, Vol. 1, 1998, p. 245-248.
- [14] Personal Communication. Teleconference between Ross Bird, David Aitken, Robert Thompson, Andrew Wild and Daryl Read. 22/6/99.
- [15] Personal Communication. Meeting with Ross Bird, David Aitken, Murray Blackwell, Brenan McCarragher and Daryl Read. Seminar Room. Department of Engineering, The Australian National University. 7/4/99.
- [16] Pierce, D. "The Quest For Commitment", *America's Network* June 1999: 34 pars. [Online]. Available: <http://www.americasnetwork.com/issues/99issues/990601/990601quest.htm>. [21 March 2000].
- [17] Potts, S. "Access Network Support Systems - An Overview", *British Telecommunications Engineering*, Vol. 14, 1996, p. 341-344.

- [18] Rogers, D. and Hand, D. "Network Measurement and Performance", *British Telecommunications Engineering*, Vol. 14, 1995, p. 5-11.
- [19] Schmersal, F. "Testing to Maintain Service Standards", *Communications News* March 1998: 17 pars. [Online]. Available: <http://www.comnews.com/stories/articles/c03hek.htm>. [21 March 2000].
- [20] Silver, B., Qian, Z., Moghe, M., Eichen, E., Dolec, J., Bhatnagar, R., Friedman, A. "TCAF: Preemptive Fault Detection in Telephone Networks", NOMS '98, Proceedings of the IEEE Network Operations and Management Symposium, IEEE, New York, NY, USA, Vol. 2, 1998, p. 523-530.
- [21] *Telstra Annual Review, 1998*. [Online]. Available: <http://www.telstra.com.au/annrep/1998/sindex.htm>. [21 March 2000].
- [22] *The Telstra Customer Service Guarantee*. [Online]. Available: <http://www.telstra.com.au/csg/>. [21 March 2000].
- [23] Waller, M., Triscari, J., Owens, R., "Performance modelling in a large engineering project", *Telecommunication Journal of Australia*, Vol. 43, No. 3, 1993, p. 65-70.
- [24] Wu, P., Bhatnagar, R., Epshtein, L., Bhandaru, M., Shi, Z. "Alarm Correlation Engine (ACE)", NOMS '98, Proceedings of the IEEE Network Operations and Management Symposium, IEEE, New York, NY, USA, Vol. 3, 1998, p. 733-742.

Appendix A

Distributions used for $\beta = 2, 3$ and 4



Figure A.2: Histogram of the number of TTDs per cell for $\beta = 3$. The distribution is unimodal and slightly right-skewed, peaking at 1 TTD/cell with a frequency of approximately 14.5.

In all simulations, the actual number of PTRs produced per correct FM/FB is generated according to the probability distributions given for each case below.

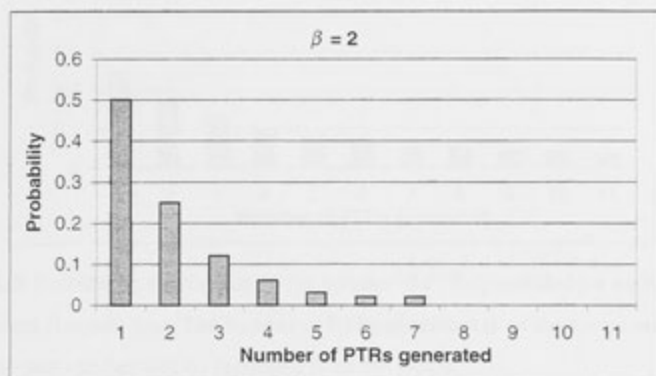


Figure A.1: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals two. The number of PTRs generated is on the x-axis and the probability that number will be generated is on the y-axis.

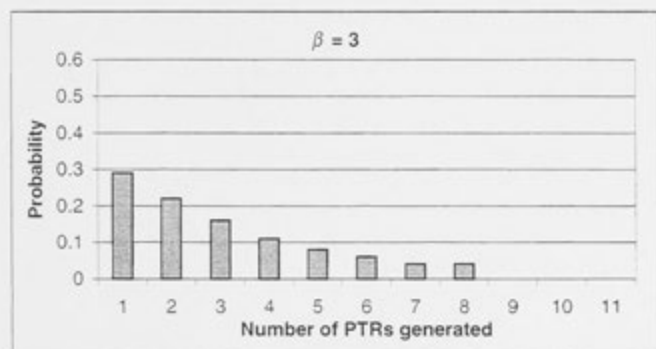


Figure A.2: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals three. The number of PTRs generated is on the x-axis and the probability that number will be generated is on the y-axis.

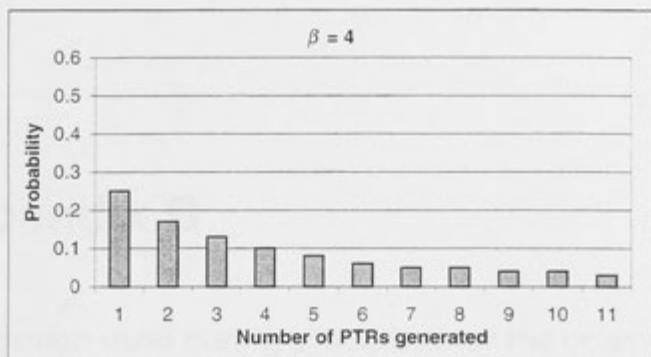


Figure A.3: Probability distribution of the number of PTRs generated for each correct FM/FB when β equals four. The number of PTRs generated is on the x-axis and the probability that number will be generated is on the y-axis.

Appendix B

Distribution used during simulation for the delay between FM/FB arrival and PTR arrival.

The distribution of the delay between the arrival of a FM/FB and the arrival of the PTR(s) it predicts that is used in the simulation results in chapter 6 can be seen below in Figure B.1

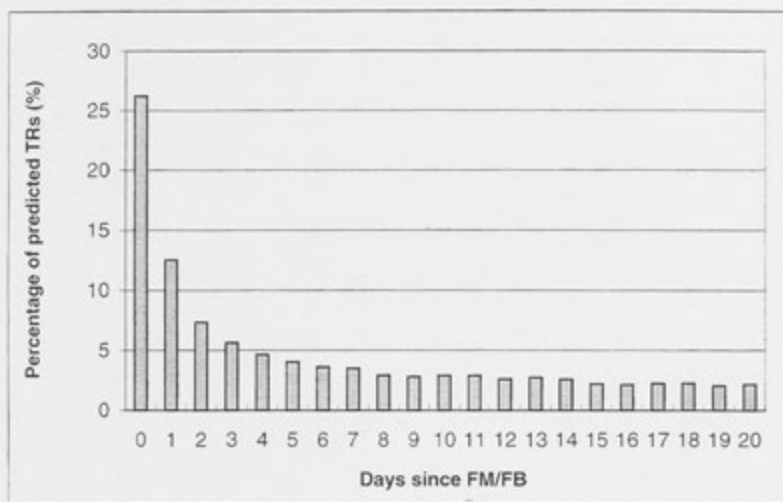


Figure B.1: Distribution of delay between FM/FB and customer PTRs. On the x-axis is the days since the FM/FB arrived and on the y-axis is the percentage of predicted TRs that arrive each day.