Use of Knowledge Intensive CAD

in Small Electrical Family Appliance Industry

Law Man Chung

A thesis submitted in partial fulfillment of the requirements for

degree of master of philosophy

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING
THE HONG KONG POLYTECHNIC UNIVERSITY
June 2004

Certificate of Originality

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written nor material which has been accepted for the award of any other degree or diploma, except where due acknowledge has been made in the text.

Law Man Chung

Abstract

Abstract of thesis entitled 'Use of Knowledge Intensive CAD in Small Electrical Family Appliance Industry"
Submitted by Law Man Chung
for the Degree of Master of Philosophy
at The Hong Kong Polytechnic University in June 2004

Many local small electrical family appliance manufacturing companies have tried to shift their business from original equipment manufacturing (OEM) to original design manufacturing (ODM) in order to get away from the price war that induced by the neighborhood underdeveloping counties including Mainland, Thailand, Malaysia, and even South America countries. However, such business migration has been largely prohibited by their incompetency in product design and development. Futhermore, the developed product knowledge is unable to retain and reuse due to the high mobility of staffing. Through literature, it was noticed that many giant and multi-national enterprises are now going, or will go, through the deployment of knowledge management (KM) technology, to enhance their new product design and development processes and shorten their new product's time to market. It was also found that, as a common believe, the development of a KM system has to involve a huge capital investment, and the process is so demanding that almost all research studies done in the area were only confined to highly complex/technology originated products including aircraft and automobile. Up to this moment, literature on application of KM for the development of simple products likes small electrical family appliance does not exist. In order to break such common believe, the research study "Use of knowledge intensive CAD in small electrical family appliance industry" that financed by the Teaching Company Scheme under the Industry Technology Fund and a local manufacturing company "General Electrical Work Corporation Limited" was set up.

The project aims to: (i) investigate how the Knowledge Intensive CAD (KIC) technology can be used as a vehicle to support the deployment of knowledge management to transfer explicit knowledge (historical data) to tacit knowledge and form a knowledge database for reuse, and (ii) to evident that KM can also be deployed by less complicated product manufacturers and used as a strategic tool to enhance their new product development capability. The argument of the research project is that through the use of a proper selected Artificial Intelligence (AI)/Artificial Neural Network (ANN) algorithm and the availability of an appropriated amount of legacy data, a knowledge database can be crystallized to predict the performance of a similar or even an entirely new design/style so that a lean and agile new product development process can be obtained. The proposed KIC methodology/roadmap composes of five phases: *(i) Decision and selection of a KIC application, (ii) Problem dissociation and identification of attribute characteristics/properties, (iii) Selection of AI/ANN algorithms, (iv) Knowledge capitalization, and (v) Knowledge deployment.* Based upon the proposed KIC development methodology/roadmap, a prototype KIC system for the design of a plastic toaster case (heating test) was developed and evaluated. Two investigations that included: (i) prediction of dedicated style with variable sizes, and (ii) prediction of an entirely new style from existing styles with the whole and divided data set input approaches were made. It was found that the temperature predictions made by the KIC prototyping system were well within the +20°C and -10°C design error limits and the throughput of processing an enquiry (prediction of a toaster case surface temperature and resultant thermal strain) could be done within eight hours. It was also evidenced that the KIC prototyping system is both capable the predictions of toaster case design of similar shape and entirely new style. The estimated time for the development of an additional KIC module would be around three months with an investment around HK$43,000 that is affordable by most manufacturing companies. The results of the project study concluded that the use of KIC to aid the product

development of the small electrical family appliance industry is feasible and efficient whilst the missing gap in between the deployment of the entirely CAE approach and traditional experience dependent method can be bridged.

Acknowledgements

The author would like to express his deepest appreciation to his academic supervisors Dr. K.H. Lau and co-supervisor Prof. W. B. Lee head of Industrial and Systems Engineering Department of The Hong Kong Polytechnic University, for their most stimulating advices on the execution of the research work.

The author would also like to thank Mr. Daniel Yip, managing director and the senior management of the G.E.W. Corporation Limited for their kindness to provide the opportunity for learning and experimenting the project. Thanks are also given to all staff in the company and its major customers for their invaluable feedback and comments on the system design and development.

Last, but not the least, the author would like to acknowledge Miss Karen Cheng and the staff in the Digital Factory, without their assistance in product development and computer skills, the completion of system design and implementation of the project would not be possible.

Table of Contents

Certificate of Originality	i
Abstract	ii
Acknowledgments	v
Table of Contents	vi
List of Figures	x
List of Tables	xix
List of Abbreviations	xx
1. Introduction	
1.1 Need of Knowledge Intensive CAD	1
1.2 Backgrounds of the Partnered Company	4
1.3 Objectives and Scopes of the Project	5
2. Literature Review	
2.1 Knowledge	7
2.1.1 Definitions of Knowledge	7
2.1.2 Classification of Knowledge	8
2.1.3 Knowledge Related Product Design and Development	9
2.1.4 Significance of Knowledge in a Manufacturing Organization	10
2.2 Knowledge Management	11
2.2.1 Definitions of Knowledge Management	11
2.2.2 Evolution of the Knowledge Management	12
2.2.3 Technological Development of Knowledge Management	13
2.2.4 Reasons for Implementing Knowledge Management	14
2.2.5 Models for Knowledge Management Development	15
2.3 Artificial Intelligence	17
2.3.1 Definitions of Artificial Intelligence	17
2.3.2 Historical Developments for Artificial Intelligence and Neural Network	17
2.3.3 Artificial Neural Network	19
2.3.4 Applications of Artificial Neural Network	25
2.4 Knowledge Intensive CAD	26

2.4.1 Origin of the Knowledge Intensive CAD (KIC) 26

2.4.2 Definitions of Knowledge Intensive CAD 29

2.4.3 Models for the Development a KIC System 30

2.4.3.1 Knowledge Capitalization Process 31

2.4.3.2 Knowledge Deployment Process 32

3. Methodology

3.1 Model for the Development of a KIC System 34

3.2 Matrix for the Decision to Set up a KIC System 36

3.3 Workflow for the Development of a KIC System 38

3.3.1 The Knowledge Crystallization Process 40

3.3.1.1 Data Collection and Conversion 40

3.3.1.2 Selection of ANN Algorithm 42

3.3.1.3 Setup of Training Schema and the Identification of the Best ANN Algorithm 44

3.3.2 The Knowledge Deployment Process 47

3.3.2.1 Developing of the Pre-Processing Application Programs for Inquiry 47

3.3.2.2 Design of the KIC System Architecture 48

3.3.2.3 Development of the Post-processing KIC Graphical User Interface 49

4 Case Study – Application of KIC for the Prediction of Thermal Displacement of a Plastic Toaster Case

4.1 Background of Study 50

4.2 Assessment/Justification for the Set Up of KIC Heating Test 51

4.3 The IEC Heating Test 54

4.4 Set Up of the KIC Investigations for the Heating Test 54

4.5 Disassociation of Problem Attributes and Properties 56

4.6 Conversion of Legacy Data to the KIC System for Knowledge Training 58

4.7 Data Analysis and Purification 59

4.8 Investigation 1- Prediction of Dedicated Model for Variable Sizes 59

4.8.1 Network Input Determination and Setup of Training Schema 63

4.8.2 The Best ANN Algorithm Selection 64
4.9 Investigation 2 - Prediction of an Entirely New Toaster Case Design from Existing Styles 68
4.9.1 Training Schema for the Fifth Toaster Case Temperature Prediction 68
4.9.1.1 Investigation I with 468 Legacy Data Sets – Multi-Style/Single Layer 69
4.9.1.2 Investigation II with 1700 Legacy Data Sets – Multi-Style/Multi-Layers 70
4.9.2 Setup of Training Schema of the Sixth Toaster Case Temperature Prediction (Multi-Style/Multi-Layers) 72
4.9.2.1 Selection of the Best NN Algorithm 73
4.10 Deployment of the KIC 74

5 Results and Discussions
5.1 Transformation of Explicit Knowledge to Tacit Knowledge 79
5.2 Performance of the KIC System for Heating Test 79
5.2.1 Prediction Accuracy of the First Investigation for a Dedicated Style and Variable Sizes 79
5.2.2 Prediction Accuracy of the Second Investigation – New Style/Multi Model 83
5.2.3 The Prediction of Thermal Displacement 91
5.3 Impacts of the Proposed KIC System 92
5.4 Technical Barrels in the Development of the KIC System 96

6 Conclusion and Recommendations for Future Development 98
6.1. Conclusion 98
6.2. Recommendations for Future Development 99

Bibliographies and References 101
Appendices 108
Appendix I - Results of the First Investigation 108
Appendix II - Results of the Second Investigation 113

Appendix III - Results of the Confirmation Investigation 118

Appendix IV - Experiment Results of the Different Toaster 123

Appendix V - System Configuration of The KIC 150

Appendix VI - List of the Published Papers 151

List of Figures

Figure 1	Main Business Streams in Hong Kong Industry (1998 and 2003)	2
Figure 2	Distribution of Product Nature in local Small Electrical Family Appliance Industry	3
Figure 3	Typical Products Produced by G.E.W	5
Figure 4	The Six-Step Knowledge Evolution Process	8
Figure 5	Product Knowledge Classification	10
Figure 6	Milestones of Knowledge Management from 1950's to 2000's	12
Figure 7	Use of Tools/Technologies in KM Development in 2000's	14
Figure 8	Evolution of Models for Knowledge Management	16
Figure 9	Nonaka SECI Model	15
Figure 10	Activation Function of the Neural Network	22
Figure 11	Roadmap for the Development of a KIC System	35
Figure 12	Cost and Risk vs Technical Complexity and Data Availability	37
Figure 13	Decision Matrix for a KIC Application	37
Figure 14	Workflow for the Development of a KIC System	39
Figure 15	Capturing of Legacy Data	42
Figure 16	Model for the Problem Decomposition and Appropriate ANN Algorithms Selection	43
Figure 17	Workflow of Network Training and Best Network Identification	46
Figure 18	Workflow of the Knowledge Deployment Process	47
Figure 19	The Architecture of the Proposed KIC System	49
Figure 20	Schematic of a Toaster Heating Test	50
Figure 21	Pareto Analysis of Toaster Functional Test	52

Figure 22	Business Distribution of G.E.W	52
Figure 23	Number of New Model Introduced	53
Figure 24	Accuracy of Using Convention CAE Approach and Proposed KIC Approach	54
Figure 25	The Six Toaster Models for Investigation	55
Figure 26	Partitioning of the Toaster Case for Temperature Input	56
Figure 27	Decision Matrix of ANN Algorithms	57
Figure 28	Decomposition of Toaster Design Problem	58
Figure 29	Recognition and Conversion Process for a 3D Geometry	60
Figure 30	Experimental Results of the Heating Profile for Different Size and Shape of Cases	61
Figure 31	Raw Data Set for the Toaster in Line 1 Location	62
Figure 32	Purified Data Set for the Toaster in Line 1 Location	62
Figure 33	Screenshot of the Neural Network Training	63
Figure 34	The Training Schemas for the First Investigation	64
Figure 35	Final Weight Distribution for the MLP and RBF Algorithms in Divided Approach	67
Figure 36	Final Weight Distribution for the MLP and RBF Algorithms in Whole Set Approach	68
Figure 37	Schema for the Investigation 2 Setup	69
Figure 38	Final Weight Distribution for the MLP and RBF Algorithm with 468 Data Set	70
Figure 39	Final Weight Distribution for the MLP and RBF Algorithm with 1872 Data Set	71
Figure 40	Generation of the Knowledge Spiral	72

Figure 41	Final Weight Distribution for the MLP and RBF Algorithm	73
Figure 42	Main Screen of the Knowledge Portal	74
Figure 43	Screen Shot of the Product Line Selection	75
Figure 44	Screen Shot for KIC System Module Selection	75
Figure 45	Screen Shot of Functional Test Selection – the Heating Test Module	76
Figure 46	Screen shot of the Help Document in Each Product Test	76
Figure 47	Screen Shot for Login - Accessing the KIC Module	77
Figure 48	Screen Shot of the Slicing Program	77
Figure 49	Screen Shot of the Retrieval of the Codified Knowledge and Execute a Prediction	78
Figure 50	Screen Shot of the Post-processing - Display of Predicted Results	78
Figure 51	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (MLP with Divided Approach)	81
Figure 52	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (RBF with Divided Approach)	81
Figure 53	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (MLP with Whole Set Approach)	82
Figure 54	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (RBF with Whole Set Approach)	82
Figure 55	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (MLP with Single Layer Approach)	84
Figure 56	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (RBF with Single Layer Approach)	85
Figure 57	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (MLP with Multi-Layer Approach)	85

Figure 58	Deviation of the Predicted Temperature Result from Line 1 to Line 9 (RBF with Multi-Layer Approach)	86
Figure 59	Deviation of the Predicted Temperature Result from Line 1 to Line 9 of Confirmation Study (MLP)	87
Figure 60	Deviation of the Predicted Temperature Result from Line 1 to Line 9 of Confirmation Study (RBF)	88
Figure 61	Standard Deviation of Difference Number of Data Sets	88
Figure 62	Testing Error of Difference Number of Data Sets	89
Figure 63	Normal Distribution of the MLP and RBF with Different Number of Training Data Sets	90
Figure 64	Normal Distribution of Difference Number of Training Data Sets	91
Figure 65	Thermal Displacement Measurement of a Toaster Case (a) by Virtual Validation and (b) by CMM	92
Figure 66	The Traditional Toaster Development Process	93
Figure 67	The Validation Time between the Traditional Product Development Process and Proposed KIC System	94
Figure 68	The Price of the Commercial Neural Network Software Package	95
Figure 69	Deviation of the Predicted Temperature of Line 1 in the First Investigation	108
Figure 70	Deviation of the Predicted Temperature of Line 2 in the First Investigation	108
Figure 71	Deviation of the Predicted Temperature of Line 3 in the First Investigation	109
Figure 72	Deviation of the Predicted Temperature of Line 4 in the First Investigation	109

Figure 73 Deviation of the Predicted Temperature of Line 5 in the First Investigation 110

Figure 74 Deviation of the Predicted Temperature of Line 6 in the First Investigation 110

Figure 75 Deviation of the Predicted Temperature of Line 7 in the First Investigation 111

Figure 76 Deviation of the Predicted Temperature of Line 8 in the First Investigation 111

Figure 77 Deviation of the Predicted Temperature of Line 9 in the First Investigation 112

Figure 78 Deviation of the Predicted Temperature of Line 1 in the Second Investigation 113

Figure 79 Deviation of the Predicted Temperature of Line 2 in the Second S Investigation 113

Figure 80 Deviation of the Predicted Temperature of Line 3 in the Second Investigation 114

Figure 81 Deviation of the Predicted Temperature of Line 4 in the Second Investigation 114

Figure 82 Deviation of the Predicted Temperature of Line 5 in the Second Investigation 115

Figure 83 Deviation of the Predicted Temperature of Line 6 in the Second Investigation 115

Figure 84 Deviation of the Predicted Temperature of Line 7 in the Second Investigation 116

Figure 85 Deviation of the Predicted Temperature of Line 8 in the Second Investigation 116

Figure 86 Deviation of the Predicted Temperature of Line 9 in the Second Investigation 117

Figure 87 Deviation of the Predicted Temperature of Line 1 in the Confirmation Investigation 118

Figure 88 Deviation of the Predicted Temperature of Line 2 in the Confirmation Investigation 118

Figure 89 Deviation of the Predicted Temperature of Line 3 in the Confirmation Investigation 119

Figure 90 Deviation of the Predicted Temperature of Line 4 in the Confirmation Investigation 119

Figure 91 Deviation of the Predicted Temperature of Line 5 in the Confirmation Investigation 120

Figure 92 Deviation of the Predicted Temperature of Line 6 in the Confirmation Investigation 120

Figure 93 Deviation of the Predicted Temperature of Line 7 in the Confirmation Investigation 121

Figure 94 Deviation of the Predicted Temperature of Line 8 in the Confirmation Investigation 121

Figure 95 Deviation of the Predicted Temperature of Line 9 in the Confirmation Investigation 122

Figure 96 Experimental Temperature Results of the First Model (Line 1) 123

Figure 97 Experimental Temperature Results of the First Model (Line 2) 123

Figure 98	Experimental Temperature Results of the First Model (Line 3)	124
Figure 99	Experimental Temperature Results of the First Model (Line 4)	124
Figure 100	Experimental Temperature Results of the First Model (Line 5)	125
Figure 101	Experimental Temperature Results of the First Model (Line 6)	125
Figure 102	Experimental Temperature Results of the First Model (Line 7)	126
Figure 103	Experimental Temperature Results of the First Model (Line 8)	126
Figure 104	Experimental Temperature Results of the First Model (Line 9)	127
Figure 105	Experimental Temperature Results of the Second Model (Line 1)	127
Figure 106	Experimental Temperature Results of the Second Model (Line 2)	128
Figure 107	Experimental Temperature Results of the Second Model (Line 3)	128
Figure 108	Experimental Temperature Results of the Second Model (Line 4)	129
Figure 109	Experimental Temperature Results of the Second Model (Line 5)	129
Figure 110	Experimental Temperature Results of the Second Model (Line 6)	130
Figure 111	Experimental Temperature Results of the Second Model (Line 7)	130
Figure 112	Experimental Temperature Results of the Second Model (Line 8)	131
Figure 113	Experimental Temperature Results of the Second Model (Line 9)	131
Figure 114	Experimental Temperature Results of the Third Model (Line 1)	132
Figure 115	Experimental Temperature Results of the Third Model (Line 2)	132
Figure 116	Experimental Temperature Results of the Third Model (Line 3)	133
Figure 117	Experimental Temperature Results of the Third Model (Line 4)	133
Figure 118	Experimental Temperature Results of the Third Model (Line 5)	134
Figure 119	Experimental Temperature Results of the Third Model (Line 6)	134
Figure 120	Experimental Temperature Results of the Third Model (Line 7)	135
Figure 121	Experimental Temperature Results of the Third Model (Line 8)	135
Figure 122	Experimental Temperature Results of the Third Model (Line 9)	136

Figure 123	Experimental Temperature Results of the Fourth Model (Line 1)	136
Figure 124	Experimental Temperature Results of the Fourth Model (Line 2)	137
Figure 125	Experimental Temperature Results of the Fourth Model (Line 3)	137
Figure 126	Experimental Temperature Results of the Fourth Model (Line 4)	138
Figure 127	Experimental Temperature Results of the Fourth Model (Line 5)	138
Figure 128	Experimental Temperature Results of the Fourth Model (Line 6)	139
Figure 129	Experimental Temperature Results of the Fourth Model (Line 7)	139
Figure 130	Experimental Temperature Results of the Fourth Model (Line 8)	140
Figure 131	Experimental Temperature Results of the Fourth Model (Line 9)	140
Figure 132	Experimental Temperature Results of the Fifth Model (Line 1)	141
Figure 133	Experimental Temperature Results of the Fifth Model (Line 2)	141
Figure 134	Experimental Temperature Results of the Fifth Model (Line 3)	142
Figure 135	Experimental Temperature Results of the Fifth Model (Line 4)	142
Figure 136	Experimental Temperature Results of the Fifth Model (Line 5)	143
Figure 137	Experimental Temperature Results of the Fifth Model (Line 6)	143
Figure 138	Experimental Temperature Results of the Fifth Model (Line 7)	144
Figure 139	Experimental Temperature Results of the Fifth Model (Line 8)	144
Figure 140	Experimental Temperature Results of the Fifth Model (Line 9)	145
Figure 141	Experimental Temperature Results of the Sixth Model (Line 1)	145
Figure 142	Experimental Temperature Results of the Sixth Model (Line 2)	146
Figure 143	Experimental Temperature Results of the Sixth Model (Line 3)	146
Figure 144	Experimental Temperature Results of the Sixth Model (Line 4)	147
Figure 145	Experimental Temperature Results of the Sixth Model (Line 5)	147
Figure 146	Experimental Temperature Results of the Sixth Model (Line 6)	148
Figure 147	Experimental Temperature Results of the Sixth Model (Line 7)	148

Figure 148 Experimental Temperature Results of the Sixth Model (Line 8) 149

Figure 149 Experimental Temperature Results of the Sixth Model (Line 9) 149

List of Tables

Table 1	Definition of Data, Information and Knowledge (1990-2000)	6
Table 2	Perspectives and the Characteristics of the Knowledge	8
Table 3	Characteristics of AI Mechanisms	39
Table 4	Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 1)	64
Table 5	Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 2)	64
Table 6	Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 3)	65
Table 7	Summary of the Network Setting and Training Results for RBF and MLP with Whole Set Approach	65
Table 8	Summary of the Network Setting for RBF and MLP with 468 Data Sets	69
Table 9	Summary of the Network Setting for RBF and MLP with 1872 Data Sets	70
Table 10	Summary of the Network Setting for RBF and MLP	72
Table 11	Summary of All the Temperature Results from Line 1 to Line 9 (Investigation 1)	75
Table 12	Summary of All the Temperature Results from Line 1 to Line 9 (Investigation 2)	79
Table 13	Summary of the Temperature Predictions from Line 1 to Line 9 for the confirmation study	82
Table 14	Thermal Displacement Comparison between Virtual Validation and Actual	92
Table 15	The Investment Cost of the KIC Development	96

List of Abbreviations

AI	Artificial Intelligence
API	Application Program Interface
BP	Backpropagation
CAD	Computer Aided Design
CAE	Computer Aided Engineering
KBE	Knowledge Based Engineering
KIC	Knowledge Intensive CAD
KM	Knowledge Management
MLP	Multi-Layer Perceptron
ANN	Artificial Neural Network
OBM	Original Brand Manufacturing
ODM	Original Design Manufacturing
OEM	Original Equipment Manufacturing
RBF	Radial Basis Feedforward

Chapter 1 – Introduction

1.1 Need of Knowledge Intensive CAD

According to the China's Tenth Five-year Plan, a series of tax reduced plan and policies had been put forward to promote her economics development in the passes three decades. China had offerred investors great competitive advantages including low land cost, cheap labour and thus the export of the Hong Kong family electrical appliance industry had rided on its upward trend from 1980 to 1999 [CIEC, 2001] and pushed forward their market segment from urban to international. However, due to the global compeition induced by the information age, the industry is now so price sensitive and the selling/exfactory price is getting lower and lower [Warwick J. McKibbin]. At the moment, manufacturing enterprises are not only facing pressure of lowering price but also the challenges from other developing countries including: Thailand, Malaysis, Brasil, South America and Mainland. With the fade out of China's open door policy and the above issues, local small electrical family appliance industry has to manifests a completely different pattern of competition. Global competition has leaded to the trunication of a new product life cycle from several years to only one to two years. According to a survey conducted by The Hong Kong Polytechnic University [Survey on Product Design in Hong Kong 2003], manufacturers of small electrical family appliance mostly are small and medium enterprise (SME) with 89% of its headoffice in Hong Kong and 85% manufacturing plants in the Pearl River Delta. Most small electrical family appliance manufacturer are still rely on experienced engineers, workers and technicans for their new product development in China. Furthermore, the turnover rate of technical staff is very high because the salary competition among manufacturing companies. Together with the stringent customer demands in product function, quality, time to market and safety issues, the pressure on their new product development process become harder and harder. It is belivered that the only way to get out such difficulty is not just adopt and make use advanced/state-of-the-art design technologies including C3P (CAD/CAM/CAE/PDM), but also the need of knowledge management is essential so that their product development capabilities can be enhanced to guarantee their success in business.

A survey done by the Hong Kong Productivity Council [Industry Study on Electrical Household Appliances Industry 1998] revealed that 46% of the total sales of the industry were generated from the original engineering manufacturing (OEM) business while 26% were come from own branded product and 28% were come from original design manufacturing (ODM) business. A survey conducted by The Hong Kong Polytechnic University [Survey on Product Design in Hong Kong 2003] also reported that the mode of business nature of the industry has been changed. The 1998 business streams distribution of OEM, ODM and original brand manufacturing (OBM) businesses were 36%, 37% and 27% respectively whilst forty-six percent of the surveyed companies had intentions to go for a change in the nature of their business in the near future, 45 % would like to change to ODM and 36% moved change to OBM (Fig. 1).

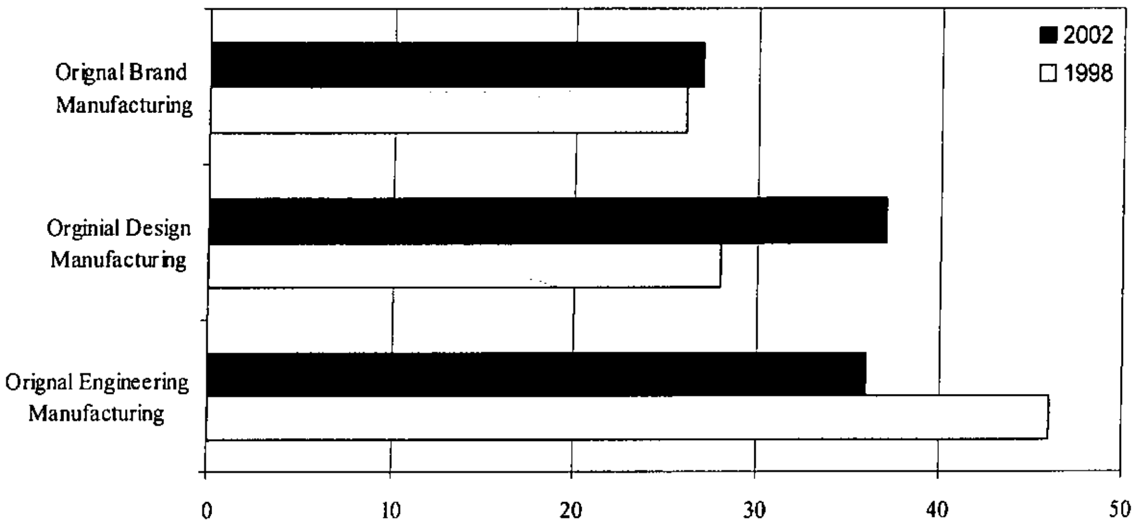


Fig. 1 Main Business Stream in the Hong Kong Industry (1998 and 2002)

(Source: Industry Study on Electrical Household Appliances Industry 1999 and Survey on Product Design in Hong Kong 2003)

However, most of the transforming companies were not able to achieve their goal and take the full advantages of such a business initiative because they are not competent enough to take up the challenges of shifting from experience dependent to a new paradigm of design and development. The Hong Kong Productivity Council [Industry Study on Electrical Household Appliances Industry 1998] found that 50% of the total output of the industry had fallen in the medium priced segment, 28% belonged to low end whilst only 22% were classified as high value added (Fig. 2). This also evidenced that there is still a big margin in the industry to move to the high end product market if the industry can equip better capabilities on both product design and processing.

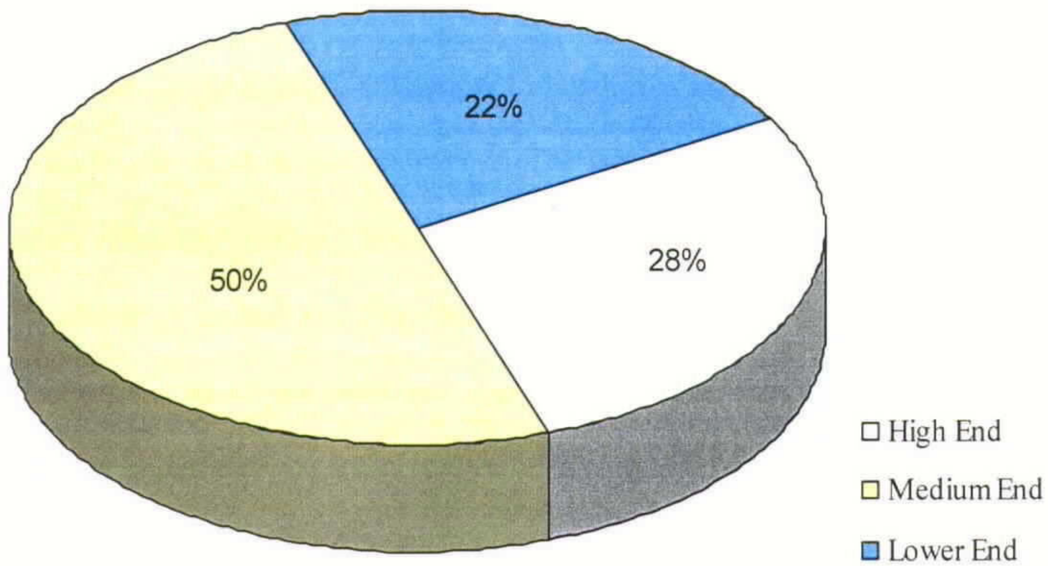


Fig. 2 Distribution of Product Nature in the Small Electrical Appliance Industry

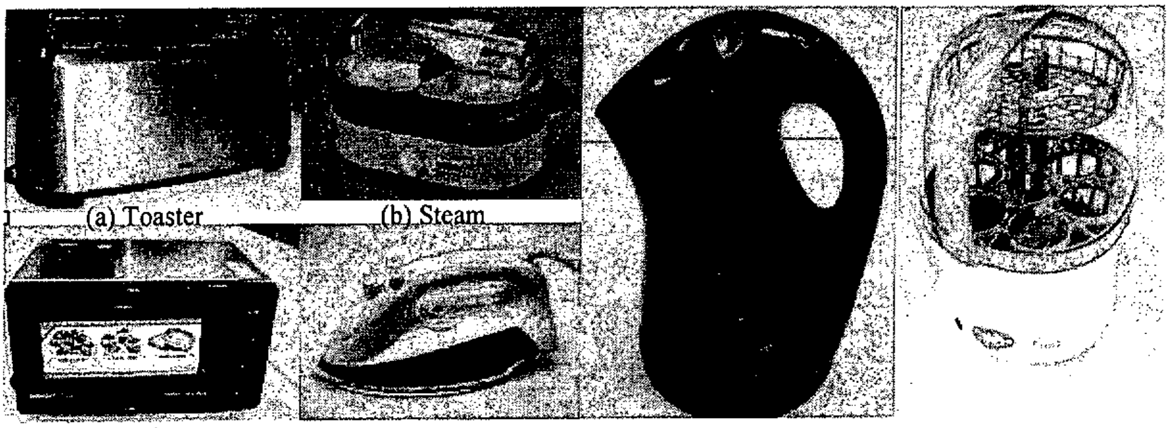
(Source: Industry Study on Electrical Household Appliance Industry 1998)

Based on the above scenarios, the manufacturing companies in the small electrical family appliance industry are facing a high-pressure environment that characterized by a number of key challenges is the only key to maintain their competitiveness by reuse of knowledge to its survival. Therefore, the project entitled "Use of Knowledge Intensive CAD (KIC) Technology in Small Electrical Family Appliance Industry" was initiated in between the

G.E.W. Corporation Limited and The Hong Kong Polytechnic University. Since traditional design process is largely depend on particular characteristic technique of skillful engineers, the study of the KIC system is to create a design tool/modules that would effectively make reuse of product information and capture and codified tacit knowledge in order to design faster and better. It was believed that the incorporation of the proposed KIC system would lead to cost and delay reduction, through the increased reuse of knowledge, and make use of ANN technology to improve their design capability and use it as a strategic weapon to aid their business transformation from OEM to ODM.

1.2 Backgrounds of the Partnered Company

General Electric Work (G.E.W.) Corporation Limited is a local owned manufacturing company of small electrical family appliances. The company was established in 1979. Her head office is located in Hong Kong with over eighthly staff whilst manufacturing plants are located in Dongguan and Shanghai with two thousand workers. The company designs and fabricates small electrical appliances that include: toaster, jug, steam iron, steam station, egg boiler, hair dryer and toaster oven (Fig. 3). The current manufacturing capacity of the company is around 3,500,000 sets of toaster, 250,000 sets of oven and 30,000 sets of steam iron per year. The company owns an asset of over HK$55 millions and it is the largest toaster supplier in the world in terms of quantity. The company has tried to shift its OEM business to ODM several years ago and is now establishing her own brand name "Welhome" in the Mainland. However, the company is now suffering from insufficient expertise in both product design and development. Even though the company got twenty-five years experience in toaster design and development, her current toaster development process still cannot guarantee a new product design to pass all the required functional tests/safety standard. Due to the global manufacturing competition, the development time of a new toaster design development time is trimmed down from nine months to only four months. Furthermore, many projects were delayed due to poor design experience and lack of manufacturing skills whilst staff turn over is so high in China that the created tacit knowledge is difficult to sustain. Problems of design and development have become the main burden that hinderes the company's business migration.



(c) Toaster Oven (d) Electric Iron (e) Jug (f) Egg Boiler

Fig 3. Typical Products Produced by G.E.W

1.3 Objectives and Scopes of the Project

The aim of the project was to demonstrate the application of knowledge intensive (KI) CAD technology can enhance a company's design competence and use as a strategic weapon to facilitate the transformation from original equipment manufacturing (OEM) to original design manufacturing (ODM). Through the acquisition of knowledge from existing legacy data and extension of its reusability with neural network, it was believe that the time to market of a new product development cycle could be largely reduced. The objectives of the project include:

(i) To establish a methodology/roadmap for the development of a knowledge intensive computer aided design (KIC) system.

(ii) To verify and evaluate the performance and feasibility of the proposed KIC methodology for the improvement of a design task including the quality of prediction and throughput.

In spite of numerous issues and areas that can be improved in a product development process, the scope of investigation was only confined to those problematic areas that experienced by the small electrical family appliance industry. Therefore, the emphasis of the study would not be put on the whole new product development cycle from concept to final design release but instead will be concentrated to the exploration of an appropriate KIC development model/roadmap to solve the burning design issues such as drop test and heating test in the industry.

Chapter 2 – Literature Review

2.1 Knowledge

2.1.1 Definitions of Knowledge

The definition of knowledge can be tracked back since the earliest civilizations. Knowledge is a very complex matter and elusive concept. Definitions for knowledge vary broadly and many famous writers had defined the knowledge in different ways and aspects. The term "knowledge" defined in the Oxford Dictionary and by Thesaurus [1980] is the *awareness or familiarity gained by experience.* The term "knowledge" has been widely used in science, engineering, technology, account etc. The definitions of data, information and knowledge had been summarized and listed in Table 1.

Table 1 Definitions of Data, Information and Knowledge (1990 –2000)

Year	Author	Data	Information	Knowledge
1990	Woolf	-	-	Organized information applicable to problem solving
1991	Nonaka	-	A flow of meaningful message	Commitments and beliefs created from this message
1992	Turban	-	-	Organized and analyzed to problem solving or decision making
1993	Wiig	-	Fact organized to describe a situation or condition	Truth and beliefs, perspectives and concept, judgment
1997	Tobin	Fact and message	Data vested with meaning	Justified, true beliefs
1997	Beckman	Data to actively enable performance, problem-solving, decision-making, learning and teaching		Reasoning about information
2000	Davenport	Davenport A set of discrete facts	A message meant to change the receiver perception	Text that answers the question why and how

To sum up, the common accepted definition for knowledge is *a piece of organized information that was important for an organization to solve a problem and make a sensible decision.* Tobin [1997] described the process of knowledge evolution consists of six levels: *(i) Data, (ii) Information, (iii) Explicit knowledge, (iv) Tacit knowledge, (v) Insight and, (iv) Wisdom* (Fig. 4), and the concept of knowledge could also be applied to manage an organization. Knowledge becomes the most important intellectual asset of an organization. Creation of knowledge and restoring wisdom of an organization has become the new paradigm of modern management.

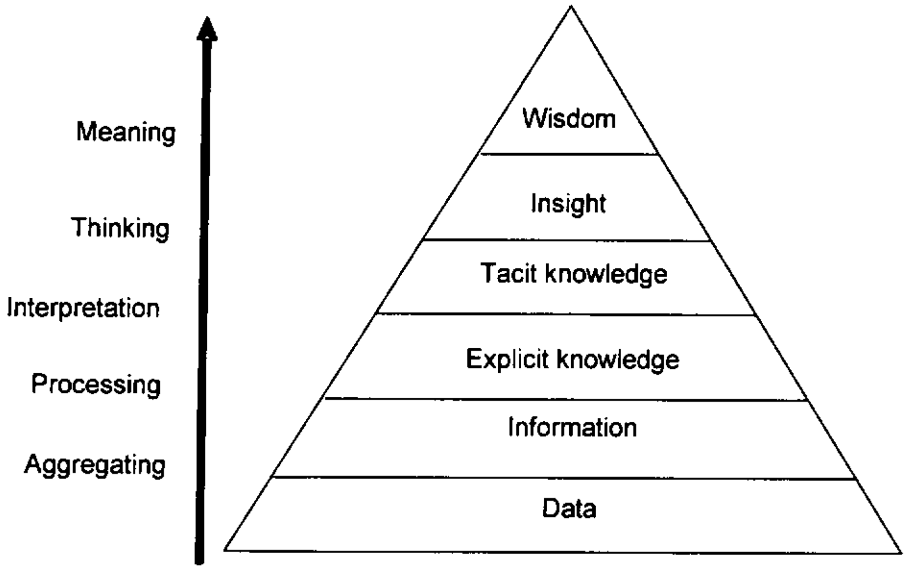


Fig. 4 The Six-Step Knowledge Evolution Process

(Source: The Knowledge Enabled Organization AMACOM, New York, N. Y.)

2.1.2 Classification of Knowledge

Table 2 summarizes all kinds of knowledge characteristics. From the table, knowledge can be divided into two main types, one is tacit knowledge and the other is explicit knowledge. Nonaka and Takeuchi [1995] pointed out that tacit knowledge is more important than explicit knowledge because it usually has more value intellectually. Nevertheless, 90% of the tacit knowledge is in the mind of the people in an organization. This knowledge will be easily lost because of the leaving of a staff, downsizing of a company or merging with other companies. On the other hand, new information will always be conceptualized in the framework of old fashioned organizational routines. Tacit knowledge and explicit knowledge were not totally separate, but mutually complementary entities. Without experience, one cannot truly understand. But, unless one tries to convert tacit knowledge to explicit knowledge, one cannot reflect upon it and share it in the whole organizational except through mentoring situations.

Table 2 Perspectives and the Characteristics of the Knowledge

Year	Author	Term of knowledge	Perspectives	Characteristics
1994	Nonaka	Tacit knowledge	Mental schemata, beliefs, images, personal points of view and perspectives, concrete know-how	Personal, context specific, subjective and experience based knowledge, and therefore, hard to formalize and communicate
1994	Nonaka	Explicit knowledge	Visible, formalized, coded in a language natural (French, English, etc.) or artificial (UML, mathematics, etc.) and can be transmitted	Can be expressed in words, sentences, numbers or formulas
1996	Grunstein and Barthès	Tangible knowledge	Data, document, etc. while intangible assets are abilities, talents, personal experience	-
1996	Grunstein and Barthès	Intangible knowledge	Elicitation to become tangible before they can participate to a materialized corporate memory	-
1998	Geoffrey Hinchliffe	Episteme knowledge	Book, paper	Can be represented in the forms of information or rules
1998	Geoffrey Hinchliffe	Techne knowledge	Human experience	Personal, hard to formalize

2.1.3 Knowledge Related Product Design and Development

In this research study, the term of knowledge will be defined as "the organized information related to the product development process in order to capturing the expertise experience and product life cycle knowledge". Such knowledge will be classified into three levels that include: (i) fundamental, (ii) design and (iii) product (Fig. 5). Fundamental knowledge comprises the basic principles, geometry, equation, generic objects, etc. Design-level knowledge represents the knowledge and experience of experts, the heuristics used to evaluate various model attributes and behavior, technologies, and abstract design process models. Product level knowledge represents product specifications, constraints, tolerances, functions, etc. Various design alternatives can be examined by using hypotheses and contexts, while the degree of completeness, precision, and certainty.

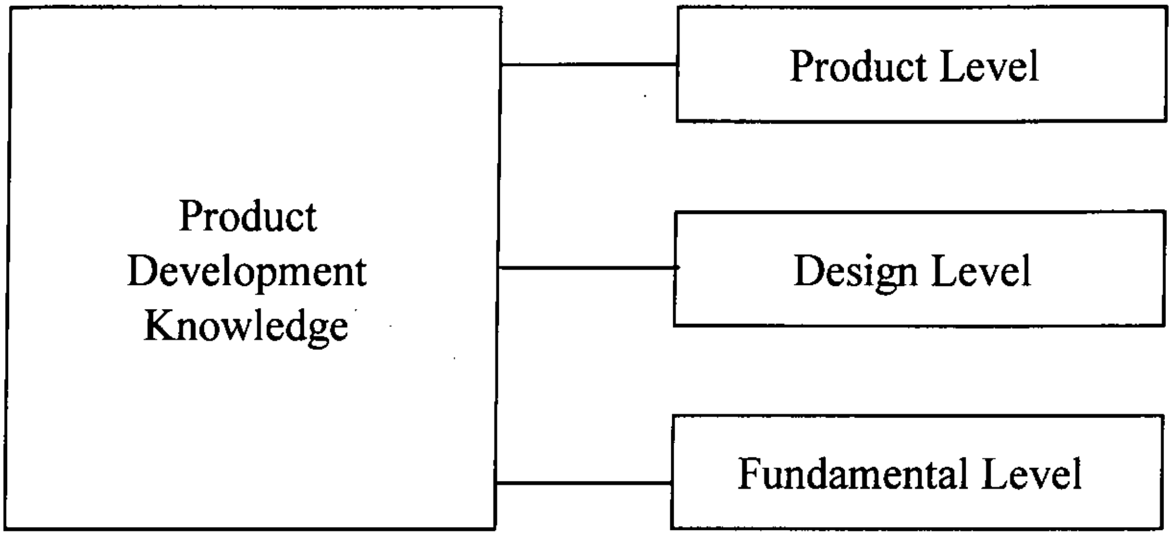


Fig. 5 Product Knowledge Classification

2.1.4 Significant of Knowledge in a Manufacturing Organization

Quinn [1996] mentioned that the success of an organization relies on the management of professional intellect. Stewart [1998] stressed that the importance of creating and managing intellectual capital to the success of an organization. Tobin [1998] claimed that networking knowledge within a company and sharing of knowledge are important. Drucker [1998] brought the important idea of knowledge worker as a measure to the competence of a company. He also pointed out that those knowledge workers nowadays are highly mobile and it can cause severe loss of knowledge if a company does not have the proper system to keep knowledge. A survey conducted by KMPG [1998] showed that 40% of the cases had serious loss of income due to the departure of employees. Stewart [2001] brought the fact that knowledge being the biggest export of the USA from 1999 and now the world is constantly make use buys and sells knowledge. To sum up all authors perceptive, knowledge assets include talent, skills, know-how, know-what, relationship and networks that embody them that can be used to create wealth, most asset depreciate from the day of acquisition and increasing their comparative advantage of a company.

2.2 Knowledge Management

2.2.1 Definitions for Knowledge Management

There exist many knowledge management definitions proposed by different authors and vary broadly. Wiig [1993] stated that a *knowledge management being a systematic, explicit, and deliberate building, renewal, and application of knowledge to maximize an enterprise's knowledge-related effectiveness and returns from its knowledge assets.* Petrash [1996] gave the definition of knowledge management as *the right knowledge to the right people at the right time so they can make the best decision.* Beckman's [1997] view on the definition of knowledge management was *knowledge management being the formalization of and access to experience, knowledge, and expertise that create new capabilities, enable superior performance, encourage innovation, and enhance customer value.* O'Dell [1998] gave definition of knowledge management as *applying systematic approaches to find, understand, and use knowledge to create value.* Tiwana [2001] defined knowledge management as *management of organizational knowledge for creating business value and generating competitive advantage.* To sum up, knowledge management can be regarded as *a set of processes from transferring intellectual capital within an organization that lead to innovation, knowledge creation, and replenishment of an organization's core competency.*

2.2.2 Evolution of Knowledge Management

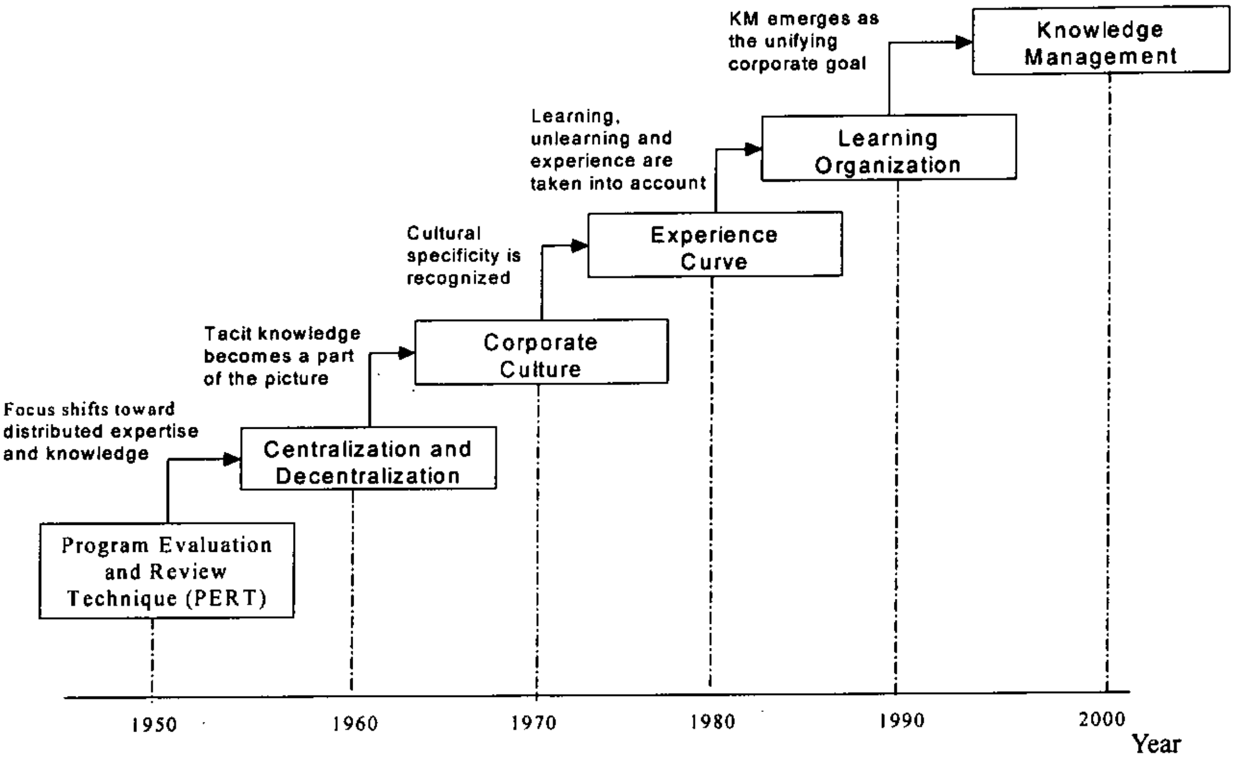


Fig. 6 Milestones of Knowledge Management from 1950s to 2000s

The term "Knowledge management" is relatively new and it is likely to become an important management tool for the coming era, however, the concept behind of knowledge management is nothing new. The major development and milestones in knowledge management from 1950s to 2000s was summarized and shown in Fig. 6. In 1950s, it was the decade associated with quantitative management techniques such as program evaluation and review techniques (PERT). In 1960s, main focus of study was on different forms of organizational structure and the effects of centralization or decentralization. In 1970s, emphasis of knowledge merge was started on the importance of teamwork, portfolio management and the experience curve. The concept of sharing knowledge within a team and understanding the cultural importance of a company was brought into the 1980s. Knowledge Management, in the 1980s, took more interest in corporate culture, learning organization, downsizing, and management by walking around (MBWA) and total quality management (TQM). The learning organization concept that emphasizes the learning and unlearning, laid the groundwork of early knowledge management development of the 1990s, Knowledge Management that sprouted the decade and it was the era for reengineering and information technologies. Furthermore, evolvement of Internet/Web based information technologies enhanced the rapid development of knowledge management. Up to now, there are two major roles accepted as a most important management tool include: (i) creation an enterprise-wide integration through a knowledge sharing culture, (ii) recognize the value of intellectual capital and understand that competition depends not on the differential possession of physical assets, or even of information, but on the ability to deploy knowledge.

2.2.3 Technological Development of Knowledge Management

Knowledge management is not just simply a development of information networking system, such as Internet or Intranet, with databases. It actually covers multidisciplinary technologies include cognitive science, expert systems and artificial intelligence, computer support collaborative work (groupware), library and information science, document management system, decision support system, relational and objects databases. Dyer [2000] reported that the most famous knowledge management systems all used the e-mail and message (Fig. 7). On the other spectrum, data warehouse that covered artificial intelligence can be used for the development of a KM system. Hence, new insights into the management of knowledge and the availability of new technology to capture and store codified knowledge offer considerable promises.

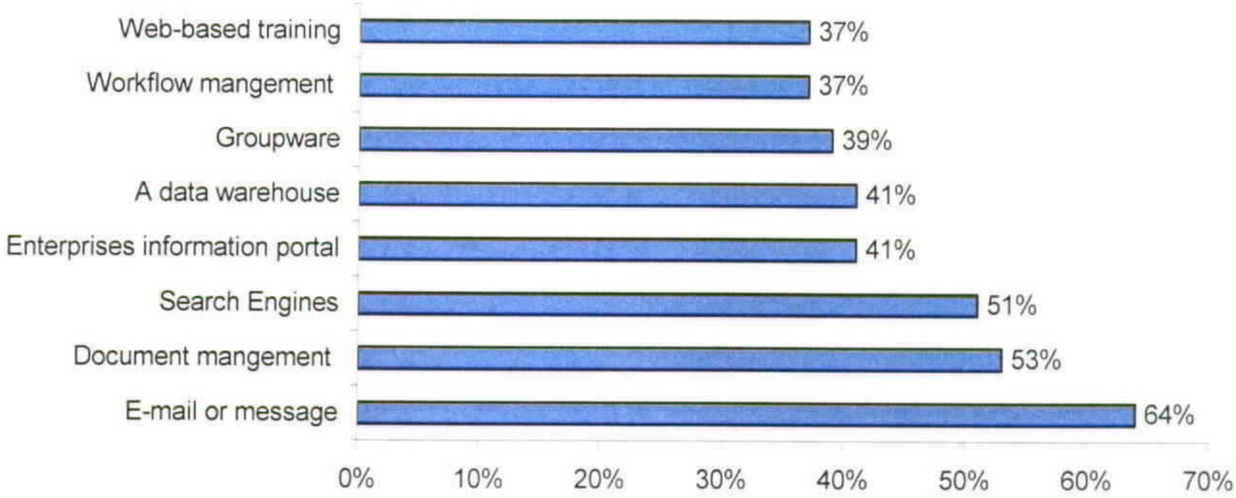


Fig. 7 Use of Tools/Technologies in KM Development in 2000's

(Source Adapted from Dyer 2000)

2.2.4 Reasons for Implementing Knowledge Management

Manufacturing enterprises are now paying more attention to knowledge management because of its competitive advantages. In a new product development process, a new product design has to be lower in cost, better in quality and faster time to market. The time to market of a new product development can reduced by not duplicating work that has been done before and the avoidance of repetitive design mistakes. The reuse of knowledge becomes the most critical success factor that can reduce expensive design re-invention. Knowledge workers should spend their time on more value-added work. Knowledge management can also improve the effectiveness of a decision-making as the reuse of past knowledge will eliminate many flawed assumptions. Proper use of knowledge management can promote systematic innovations and hence increases the creativity within a company. Furthermore, knowledge retention within a company can build up its own "knowledge base" or "institutional memory". Thus, a well-managed knowledge management system has to be deployed in order to effectively maintain the explicit and ideally the tacit knowledge generated from a project or problem. Such knowledge can then be reused and shared for other projects and finally becomes a tangible asset of a company.

2.2.5 Models for Knowledge Management Development

Many authors contributed in the study of knowledge management and developed different frameworks on modeling knowledge management. Fig. 8 shows the historical knowledge management development models from 1990 to 2000. The focus of knowledge management development in the early days of data storage has been evolved to the later stage of creating and selling of knowledge. One of the important knowledge creation concepts - "knowledge spiral" was introduced by Nonaka [1991]. His model of socialization, externalization, combination and internalization (SECI) shows the knowledge transfer process within a company (Fig. 9).

(i) *Socialization:* Sharing experience and creating tacit knowledge

(ii) *Externalization:* Concept creation and triggered by dialogue or reflective reflection, articulating tacit knowledge into explicit knowledge

(iii) *Combination:* Categories and integrating explicit knowledge.

(iv) *Internalization:* Embodying explicit knowledge into tacit knowledge.

Explicit	**Combination** Knowledge Transfer	**Internalization** Knowledge Internalization
Tacit	**Externalization** Knowledge Transfer	**Socialization** Knowledge creation
	Explicit	Tacit

Fig. 9 Nonaka's SECI Model

Task	Year	Author	1st stage	2nd stage	3rd stage	4th stage	5th stage	6th stage	7th stage	8th stage
Storage and Capitalization	1993	Wiigs	Creation and souring of knowledge	Compilation and transformation of knowledge	Dissemination	Application and value realization				
	1996	Van der Spek and Spijkervet	Developing new knowledge	Securing new and existing knowledge	Distributing knowledge	Combining knowledge				
Networking and Sharing	1996	Marquardt	Acquisition	Creation	Transfer	Utilization				
	1997	Ruggles	Generation of knowledge that	Codification	Transfer of knowledge					
	1997	Holsappe and Joshi	Knowledge acquisition	Selection of knowledge	Knowledge internalization	Using knowledge	Knowledge generation	Knowledge externalization		
Knowledge Creation and Sell	1998	Liebowitz and Beckman	Identify	Capture	Select	Store	Share	Apply	Create	Sell and brought
	1999	Junnrakar	Connection of people with other knowledgeable people	Connection of people with information	Conversion of information to knowledge	Encapsulation of knowledge and make it easier to transfer	Dissemination of knowledge around the firm			
	2000	Liebowitz	Transform information into knowledge	Identify and verify knowledge	Capture and secure knowledge	Organize knowledge	Retrieve and apply knowledge	Combine knowledge	Create knowledge	

Fig. 8 Evolution of Models for Knowledge Management

To sum up, it is worthwhile to mention that most of these models have the similar concept for knowledge management and their works were heavily concentrated on the information networking, sharing and selling. There is no specific model that can be resume for NN product design and development process.

2.3 Artificial Intelligence

2.3.1 Definitions of AI

"Artificial intelligence (AI)" stated that is the part of computer science concerned with designing intelligent computer system [Barr and Feigenbaum 1981], that is, systems that exhibit the characteristics associated with intelligence in human behavior – understanding language, learning, reasoning, solving problem and so on. In other words, AI is concerned with programming computers to perform tasks that are presently done better by humans, because it involves such higher mental processes such as perceptual learning, memory organization and judgmental reasoning [Minsky, 1968]. One well-publicized definition of AI is behavior by a machine that, if performed by a human being, would be called intelligent [Rich and Knight, 1991].

2.3.2 Historical Development of Artificial Intelligence and Neural Network

In the past sixty years, AI had undergone substantial ups and downs. The birth of AI was in the early 1940s whilst the central nervous system was regarded as the first work recognized in the AI field [Warren McCulloch and Walter Pitts, 1940]. Johnson Neumann [1951] introduced the first neural network computer and John McCarthy [1958] brought together researchers interested in the study of machine intelligence, artificial neural nets and automata theory to form the Dartmouth Conference Workshop that gave birth to coin artificial intelligence. AI was considered as a valuable tool to support a decision making and regarded as great ideas with great expectation in 1960s. Frank Rosenblatt [1962] proved the perception convergence theorem and demonstrated that his learning algorithm could adjust the connection strengths of a perception. In 1965, Loft Zadeh published his famous paper "Fuzzy sets'. Bryson and Ho [1969] introduced a back-propagation learning algorithm. However, AI was disillusioned and funding cutback in the early 1970s and the pace of AI was slow down. Until the last two decades (1980s - 1990s), the development of preliminary binary model had brought AI to a more mature expert technology and could be applied in different areas. In the 1980s, because of the need for brain-like information processing, as well as the advances in computer technology and progress in neuroscience, the field of neural network experienced a dramatic resurgence. Major contributions to both theory and design were made on several fronts. Grossberg [1980] established a new principle of self-organization (adaptive resonance theory), which provided the basis for a new class of neural networks. In 1982, the Hopfield's theory introduced neural networks that attracted much attention in the 1980s. In addition, Kohonen [1982] published a paper on self-organized map. Sutton and Anderson published their work on reinforcement learning and its application in control. In 1986, Rumelhart and McClelland in parallel Distributed processing: Explorations in the microstructures of cognition. Paker and LuCun [1987] developed Back-propagation learning algorithm. Since then back-propagation has become the most popular technique for training multilayer perceptions. In 1988, Roomhead and Lowe found a procedure to design layered feedforward network using radial basis functions, an alternative to multilayer percetron. In the meantime, Tuevo and Kohonen introduced his Learning Vector Quantization (LVQ) at Helsinki

Technical University to give further motivation to the family of unsupervised neural network and family of supervised models of the multi-layer percetron. A flexible form of non-linear regression known as Generalized Regression Neural Network (GRNN) was developed by Donald Specht [1991]. The concept of the network is to make use of the probability density function of the data in order to eliminate the necessity of a functional form. Kandel and Langholz [1992] had promoted a hybrid system. The integration of neural network with knowledge based like expert system was presented by Gallant and Fu in 1993 and 1994 respectively.

2.3.3 Artificial Neural Network

Since the focus of this research study was to develop an AI application in studying a multidiscipline/non-linear design problem and based on the characteristics, advantages and disadvantage comparison, the use of the artificial neural network is the most appropriate AI algorithm for the system development. Therefore, an in-depth study of the neural network algorithms had been carried out. An artificial neural network (ANN) is an information processing paradigm inspired by the way biological nervous systems, such as the brain, processing information. Each neurons is composed of three basic components: (i) the cell body, (ii) the dendrites and (iii) the axon, ANN can be looked as 'physical cellular system which can acquire, store, and utilize experiential knowledge [Davis Garson, 1998]. ANN has been applied to solve or define an increasing number of complex reasoning problems that is too complex for conventional technologies-problem or do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In addition, nonlinear programming methods (e.g. CAE) may need prohibitive amounts of CPU time for calculation and ANN easily overcomes such a problem. The prediction of a complex problem can be acquired by an ANN through a learning process. The inter-neuron connection weights known as synaptic weight are used to store the knowledge. Therefore, the ANN can be used for the handling of a complicated problem and represent by the "black box knowledge".

The development of an ANN system involves five stage: (i) Determination of the input and output processing unit, (ii) Formulation of the activation function, (iii) Design for network size and connectivity, (iv) Characteristic and application of the ANN algorithm, and (v) ANN learning process hierarchy.

(i) Input and output processing unit

The building block of a neural network is the processing unit, other terms called as a perceptron, node, or unit. While some units (e.g. input and output) do represent specific constructs or variables others (hidden unit) do not have an assigned meaning. The output function of a processing unit determines the signal that is to the passed to other unit in the network. In some cases, the output function is the identify function and the output of the unit at any time is equal to its activation at that time. In some cases, the output function is binary, bipolar or, a nonlinear function similar to the activation functions within nodes.

(ii) Formulation of the activation function

An activation function that combines the signals entering a unit with the current state of that unit to produce a new level of activation for the unit. Then, the incoming signal is evaluated by an activation function and the output of the activation function determines the state of the activation of the processing unit at a specific time. Activation function can take many forms. Four representation functions are shown in Fig. 10. The sigmoid function acts as an output gate that can be opened (1) or closed (0). Since the function is continuous, it also possible for the gate to be partially opened (i.e. somewhere between 0 and 1). Models incorporating sigmoid transfer functions often help generalized learning characteristics and yield models with improved accuracy. Use of sigmoid transfer functions can also lead to longer training times. The Gaussian transfer function significantly alters the learning dynamics of a neural network model. Where the sigmoid function acts as a gate (opened, closed or somewhere in-between) for a node's output response, the gaussian function acts like a probabilistic output controller. Like the sigmoid function, the output response is normalized between 0 and 1, but the Gaussian transfer function is more likely to produce the "in-between state". It would be far less likely, for example, for the node's output gate to be fully opened (i.e. an output of 1). Given a set of input to a node, the output will normally be some type of partial response. That is the output gate will open partially. Gaussian based networks tend to learn quicker than sigmoid counterparts, but can be prone to memorization. The hyperbolic function counterparts to the sigmoid and gaussian functions are the hyperbolic tangent and hyperbolic secant functions. The hyperbolic tangent is similar to the sigmoid but can exhibit different learning dynamics during training. It can accelerate learning for some models and also have an impact on predictive accuracy. Experimenting with transfer functions for each individual model is the only conclusive method to determine if any of the non-sigmoid transfer functions will offer both good learning and accuracy characteristics. For most modeling tasks, the sigmoid function should at least be a baseline model to measure results. A general rule of thumb is that the sigmoid will produce the most accurate model but the learning will be slower. If one intends to frequently train similar models and training speed is critical, different combinations of transfer functions, including hybrid networks, are worth investigating to find out the faster training models that exhibit acceptable accuracy.

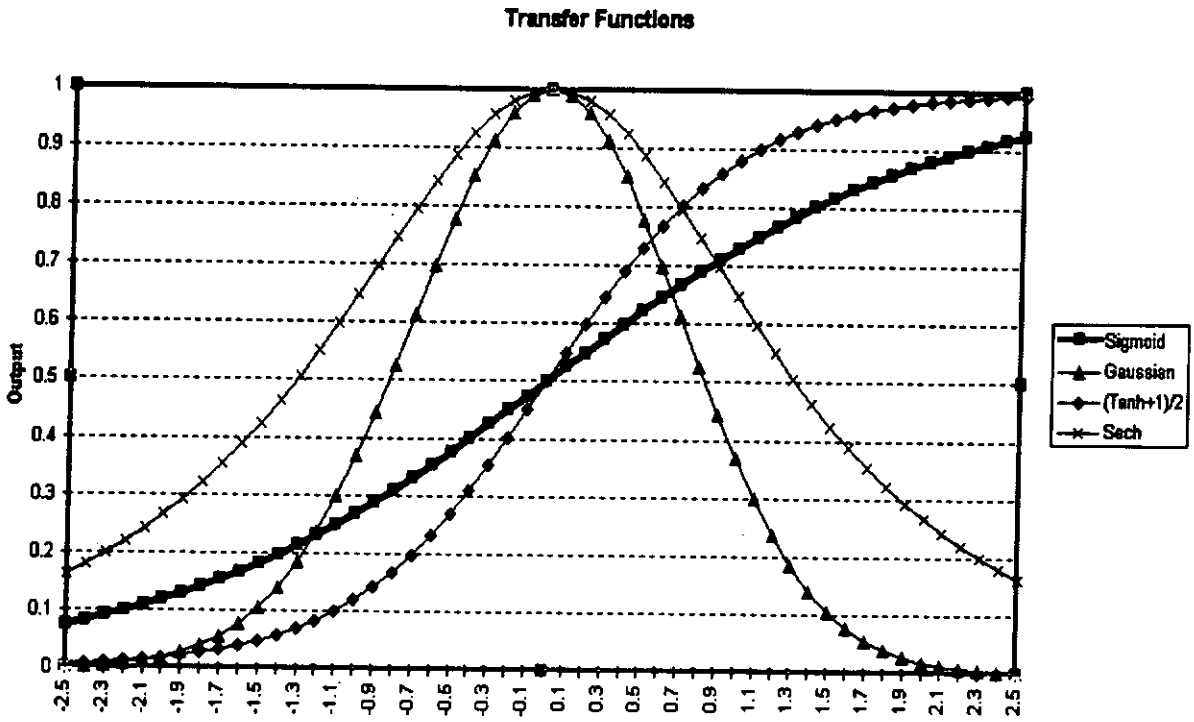


Fig. 10 Activation Function of the Neural Network

(iii) Design for network size and connectivity

The ANNs are made up of highly connected parallel processing units or nodes. These nodes are generally arranged in layers in the network. Basically, an ANN must have a minimum of two layers (input and output) but can have any number of hidden layers that often becomes a source of confusion when defining the number of hidden layer in a network. In this study, a network with an input and an output layer is referred to as a single layer network. At first glance this may appear counterintuitive, but the convection is to only enumerate layers where processing occurs. Since the input layer does not perform any processing, it is not counted in the number of layers in the network.

A Hidden layer is a layer of nodes located between the input and output layer. Units can be connected either in a feedforward or feedback system. In a feedforward system, units are only connected to unit lying in higher layers. Signals are transferred from the input layer nodes to hidden layer nodes and from hidden layer nodes to output layer nodes. A fully connected feedforward network is a special case of neural network that is often used. In fully connected feedforward networks, each node is obtained to every node in the next higher layer. A neural network can consist of multiple layers of neurons interconnected with other neurons in the same or different layers. A neuron's connection topology with other neurons can be in the same or different layers. A neuron's connection topology with other neurons may also vary from fully connected to sparsely or even locally connected. Each layer is referred to as an input layer, a hidden layer, or an output layer.

(iv) *Characteristic and application of the ANN algorithm*

The ANN learning procedures are usually divided into two categorizes: supervised and unsupervised. In supervised learning, a target vector is available which defines the desired output of the network for a given input vector. A learning algorithm is then used to adapt the weight such that the desired outputs are reproduced when the input vector is propagated through the network. Weights are adjusted iteratively according to the network chosen learning rule as training data propagates through the network. Each weight change is called an iteration and each pass through a training processing unit is called an epoch. Unsupervised learning is performed in the absence of a desired or target output vector. Only input value is supplied in the unsupervised training process. Without target output values are provided, an ANN will undergo self-organization without refereeing to the error of deviation from a desired value. Through repeated training iterations, input nodes that are similar in activation form clusters in the output nodes. For this reasons, ANNs that incorporated unsupervised learning are often called self-organization systems. The network learns to respond to patterns or cluster in the training data without any a priori specification of output classes or categories. There are a variety of applications in a new product development process for both supervised and unsupervised learning paradigm. For example, unsupervised neural network could be used to discover clusters of both independent and dependent variables as data reduction techniques similar to exploratory factor analysis. Form these clusters, a supervised neural network could be built to discover the relationships between the clusters of independent (input) variables and dependent (output variables). Independent variables factors that are thought to be related to successful development and dependent variables could be various measures of success or failure. To sum up, in supervised learning, a correct output/answer for each input pattern is supplied to the model. That is, the desired target response for the vector of training cases is also presented to the network, allowing network weight to be adjusted not only in response to the training vector but also on the basis of an error signal defined by the target vector. The Backpropagation, Multi-layer Percetron, Radial Basis Feedforward, Non-linear Generalized Regression and Adaptive Resonance Theory (ART) neural network algorithms are grouped into the supervised learning. Unsupervised learning is a process which is automatic, with classification depending on induction from examples in the training data set without reference to expected correct classification, i.e. network trained by unsupervised learning cluster input examples according to similarity. The self organizing map and the Hopfield network are grouped into the unsupervised learning category.

(v) ANN learning Process Hierarchy

The focus of this study is aimed to the development of ANN application that can be apply to the new product development process, therefore, there exist many exotic and unique learning algorithms and learning paradigms that cannot be categorized within the hierarchy. Most of the popular learning rules and learning paradigms have their focus in this hierarchy. Numerous extension and adaptations to the basic architectures exist and are still being developed. Hundreds of learning rules have been published in relevant neural network journals in the past few years. Unfortunately, once they are published, little work is done to benchmark each other to determine the specific advantages and disadvantages of individual methods. Many of these algorithms are developed either to solve a very specific application or to provide linkages between artificial neural network and biological neural network. Since, an in-depth analysis of the nuances associated with each of the numerous extensions in not the goal of the study, only a limited number of well established and commonly used ANN methods and structures will be incorporated into the application studied here.

2.3.4 Applications of the Artificial Neural Network

Over the years, this was grown and developed into a prominent philosophy in marketing and engineering, where the customer is the key to success of an organization and its new product development (NPD). The artificial neural network is a highly connected parallel structure that is a new paradigm of computing. Based on the pre-defined instructions, information is processed in a sequential way traditionally. However, with the introduction of the artificial neural network, information can be processed in a parallel way without the necessity of the predefined instructions. As a result, artificial neural network has a wide variety of applications. In recent years, some researchers and the manufacturers are adopting a neural network to tackle the non-linear design problem. Fred F. Farshad [2000] using artificial neural network to predict the temperature profiles in producing oil wells. Zamarreno [1998] used artificial neural network to provide high quality control in the presence of non-linearity. Up to this moment, the ANNs are useful in the application of prediction, classification, fault detection, time series analysis, diagnosis, optimization, system identification, and exploratory data analysis.

2.4 Knowledge Intensive CAD

2.4.1 Origin of KIC (Knowledge Intensive CAD)

In 1963, a paper presented by an MIT research group proposing a system that is now thought as the origin of Computer Aided Design (CAD) system proliferated to a great number afterwards [Sutherland]. This concept was revolutionary and stimulated many other researchers to commence the studies on theories and methodologies for manipulating geometrical shapes in computers. Therefore, from 1980's to 1990's, computational geometry is established on which many of the practical CAD systems are methodologically dependent. In 1975, The first times when significance of AI for CAD was pointed out was at a conference that was held in 1977 under the title of "Artificial intelligent and CAD" and this could said to be point at which AI and CAD were first married [Lsatombe]. In 1984, the International Federation for Information Processing (IFIP) Working Group 5.2 decided to organize three successive workshops on "Intelligent CAD" and defined in three different ways.

(i) CAD that assist designers through all stage of the design process (totally),

(ii) CAD that assists designers in the design process for any design object (flexibility),

(iii) CAD that can be counted with any other information processing system, such as CAM (integration).

In 1985, a working conference on "Design Theory for CAD" was held by the IFIP WG5.2, where it was concluded that design theory is a requisite for correct utilization of useful results of AI researchers when developing new CAD systems and CAD should an assist designer in the creative process of a design [Yoshikawa, H. and Warman, E A]. Such proceeding was the result of the first workshop held at Cambridge, MA. U. S. A in October 1987 under the subtitle of "Implication of AI and CAD". Three major topics were discussed in this workshop that included: (i) Domain type mechanical, architectural and electrical design, (ii) Artificial intelligence and (iii) computer science. The second workshop was held in Cambridge UK in 1989 and the definition of Intelligent CAD (ICAD) is introduced by Tony Holden. Tony concluded that the future ICAD system has desire to make CAD tools for easier design within their own specialties. However, all have to solve common problems of representation and reasoning and require a framework within which design descriptions can be assembled and interpreted of both human designer and computer assistant. An ICAD system should be very 'open' providing an environment within which a designer may rapidly explore many possibilities but without the fear of becoming overwhelmed by a mass of tedious detail or of coming up against hurdles imposed by the implementation technology. It is often advocated that large scale knowledge bases are useful for engineering application including design, manufacturing, operation, and maintenance, because these activities require an extremely huge amount of and various kinds of knowledge [Forbus]. Perhaps, a new paradigm has to be looked at which is based on less production with more added values [Tomiyama1993]. This paradigm requests a new way generating added values. Since benefits can be generated only from knowledge, and obviously more knowledge is needed in various aspects of engineering. In 1990, Takeda built a CAD system that integrates and made flexible use of various kinds of design knowledge and that intelligently assists the designer by giving advises, suggestions, and checking error s based on design process knowledge. In 1995, the first Knowledge Intensive CAD (KIC) workshop was held in the Helsinki University of technology espo in Finland. The aim of the workshop was to clarify and elaborate the concepts of knowledge intensive design and CAD by providing an international forum for mutual discussions and exchange of opinions of experts in the field The concept focused on exploring the concept of knowledge intensive design as a part of knowledge intensive engineering activities. The workshop discussed a variety of issues related to KIC; Knowledge intensive CAD framework, produce and design process modeling and methodologies, tools and techniques for knowledge intensive CAD. The second workshop was held at Carnegie Mellon University, Pittsburgh, USA [1996] aimed to examine architectures, representation, delivery system and methodologies for "knowledge intensive CAD" based on the results of the first workshop. The third workshop was held at the University of Tokyo, Japan, [1998] that focused on the ontology (KIC), Knowledge Intensive Design (KID), knowledge representation and applications of knowledge intensive CAD systems whilst the fourth KIC workshop was held at the University of Parma, Italy [2000] that looked into the evolution of knowledge intensive design for the life cycle, architectures, tool, methodology implementation and application of KIC. The fifth workshop was hosted by the Department of Manufacturing Engineering of the University of Malta in Malta [2002] that looked into tools developed as a result of the previous workshops and extended its focus on the KICAD architectures to provide support during different design stages.

2.4.2 Definitions of Knowledge Intensive CAD

The basis of knowledge Intensive CAD is that intensive life-cycle knowledge regarding product and design processes must be incorporated in the center of a CAD architecture. Many knowledge intensive CAD researchers define Knowledge is the set of all information, which can be brought to bear on a problem and a KIC system consists of commonly accessible knowledge sources, which can be applied to relevant problem, where a knowledge source consists of suitably structured knowledge to tackle a specific problem. A KIC system consists therefore of rules of expertise, analysis processes, standard, regulation and such likes [K.J.MacCallum 1987]. Knowledge intensive engineering is a new style of engineering based on intensive use of various kinds of engineering knowledge in various produce life cycle stages conducted with more knowledge in a flexible manner to create more added value. Knowledge intensive design boils down to integration and management of various kinds of models to synthesize an artifact, to analyze its properties, and to evaluate its performance against requirement under certain circumstances". The knowledge systemization consists of the following processes via setting up a view, articulation, codification, crystallization, verification, and reusing and sharing of knowledge [Tomiyama et al.1994]. The concept of KIC advocates that intensive life-cycle knowledge regarding product and design processes must be incorporated in the center of a CAD architecture. The KIC concept focuses on the systematization and sharing of knowledge across the life-cycle stage and organizational boundaries. KIC is a field of study that focuses on developing computational techniques for performing complex design tasks [Tomiyama 1998]. The development of a KIC system is to create a design tool that will effectively make reuse of product knowledge at many levels, starting with the functional specification and overall design rationale and ending with individual product modules, components, and their technical and geometric details.

2.4.3 Model for the Development a KIC System

The concept of knowledge intensiveness does not cover only the intelligence of a CAD system but also the intelligence of a product designed on a CAD. Mantyla [1994] mentioned that KIC has to be to address the issues of information exchange between various stages of the core and support processes: the processes and their supporting tools are designed to support and take advantage of knowledge flow. In addition, he also thought that the development of a knowledge intensive CAD system, two main steps that include (i) knowledge capitalization and (ii) knowledge deployment. Common criterion of the establishment/construction of a KIC system include:

(i) Capture and reuse of existing information at many levels, starting from the functional specifications and overall design rationale and ending with individual product modules, components, and their technical and geometrical details.

(ii) The intensive life-cycle knowledge regarding products and design processes must be incorporated in the center of the CAD architecture.

2.4.3.1 Knowledge Capitalization Process

The knowledge capitalization is a methods/process for collecting meaningful data and converting into reusable knowledge database. When codified a set of reusable knowledge through the capitalization process, four important factors should be taken into consideration,

(i) *Format decision*

Design information created and utilized must be captured in a computer intelligible form. To make the codified knowledge reusable, it must first be abstracted and generalized in a reusable format.

(ii) *Selection of design information*

Design history or design trace must be extracted during the execution of a design process, resulting a design rationale representation that preserves the design intent, reasoning and decisions of the designer.

(iii) *Data preparation and purification*

Before the capitalization process, data preparation and purification is needed to filter out error/noise of a data set.

(iv) *Graphical user interface*

User interface of the KIC system has to be user friendly, designers should not be unduly burdened by knowledge capitalization activities. In addition, knowledge representation has to flexible enough to cater the inclusion of information in variable formats, including text and image.

2.4.3.2 Knowledge Deployment Process

The other major process for the development of a KIC system is knowledge deployment. The knowledge deployment is a system development for locating, accessing and applying codify knowledge during the design, manufacturing, or other life-cycle stages of a product. A KIC developer has to be based on a problem nature, its properties and requirements to deploy a suitable knowledge database for a particular design tasks. Through the knowledge deployment process, four important elements have to be taken into consideration:

(i) *Graphical User Interface*

Throughout a product development cycle, locating and using reusable knowledge is more difficult than recreating the knowledge, therefore little reuse will take place. An user friendly graphical user interfaces that can incorporate tools and concepts of computer-supported co-operative systems and supporting various protocols for negotiation, decision making, etc has to be developed.

(ii) *Format of the codified knowledge*

The codify knowledge format has to be modified easily and augmented to make it useful in any detail context.

(iii) *Authorization and level of abstraction*

Since engineers' disciplines need form various to assess product information at different levels of abstraction and aggregation, a systematic way to distribute the required knowledge to a user is a critical success factor.

(iv) *Conceptual mapping*

The concepts that used by various people can be genuinely different. The concepts to describe a product from design viewpoint (functions, behaviors, structures) will be different from those used from analysis or manufacturing viewpoint (features geometry, manufacturing processes). Therefore, a concept standardization mapping has to be taken place.

Chapter 3 Methodology

3.1 Model for the Development of a KIC System

Based on the literature review, observations from the new product development practices of the partnered company and the knowledge intensive CAD principles, theories and the general requirements of national standards, a KIC new product development process model for the small electrical family appliance was developed and shown in Fig. 11. The intension of the roadmap for development is to provide a structured guideline/ best practice that any interested parties can refer and follow to develop a KIC system to suit their own new product development application(s), so that a design problem that involves multi-discipline and non-linear characteristics can be solved in a much efficient and cost effective way.

The methodology/roadmap starts with the break down of a product's customer requirements (CRs) into its functional requirements (FRs), then decompose into their corresponding design domains (DDs) and subsequent process domains (PDs) through the use of the Axiomatic Design theory [Nam. P. Suh]. Through the use of the zigzag mapping process, design parameters are mapped and transferred to functional requirement tests such as drop test, heating test and so on for design validations. In this model, attentions have to be paid on the success of mapping the design domain to the functional requirement tests. Once all the tests for FRs have been identified, a decision matrix should then be constructed to determine whether there exists any margin/opportunity for the development of a KIC system for a particular design application. If the answer is no, then conventional computer aided engineering (CAE) /finite element analysis and physical prototyping techniques would become the more feasible/appropriate solution to appraise the fulfillment of the functional requirements. If the decision is yes for the development of a KIC system, then the knowledge crystallization and knowledge deployment processes can then be initialized to develop the required system.

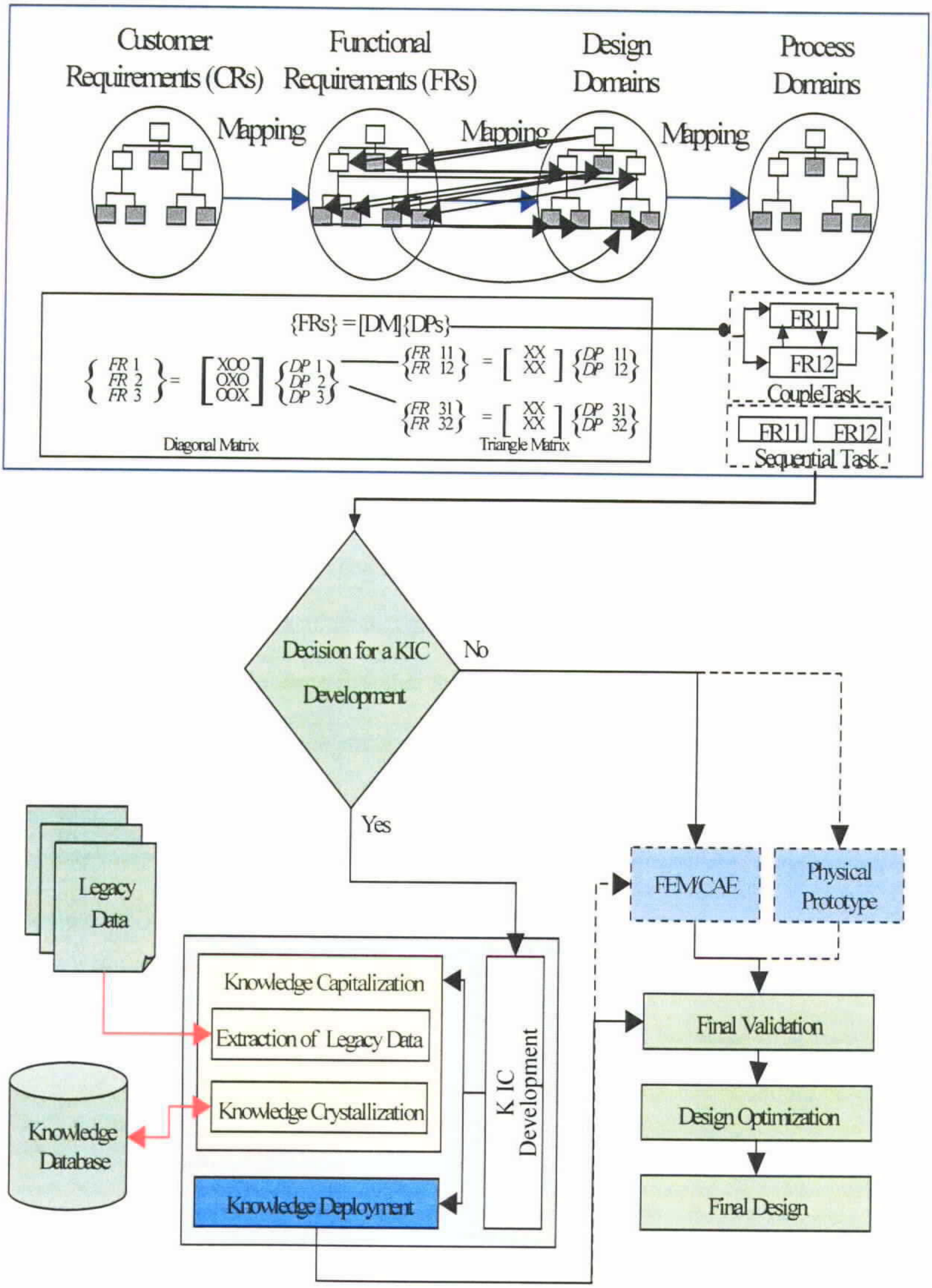


Fig. 11 Roadmap for the Development of a KIC System

3.2 Matrix for the Decision to Set up a KIC System

Even through the use of a KIC system seems like a very attractive and beneficial solution to handle a highly complex design problem, it is strongly not recommended to apply KIC to solve every product design problem by such approach. The way to appraise a design problem whether it is desirable optimized for an application, a decision matrix has be constructed to aid the KIC decision so that the risk, cost and benefits for the application can be compromised (Fig. 12 and 13). The technical complexity of a product design problem can be classified into three types that include (i) product data filtering, (ii) data enhancement and (iii) knowledge development. The data availability for an application can vary from complete to rare whilst the technical complexity of data handling also increases from data fitting to design enhancement and then to knowledge development. If data availability is rare and the technical complexity becomes much higher, under such scenario, it is highly not recommended to use KIC approach to handle design problems of such kind. Even though in some case that the complexity of a design problem is so highly, insufficient data will lead to a much greater risk in development and the demand of additional data requires excessive resources. Therefore, the availability of legacy data and the complexity of a design problem will determine the development cost and the directly influence the risk of a KIC system development. The most favorable scenario for the application of KIC is a design problem with both high technical complexity and the availability of data is plenty. In a nutshell, a balance among the technical complexity of a design task, availability of the legacy data, development cost and risk of failure has to be made.

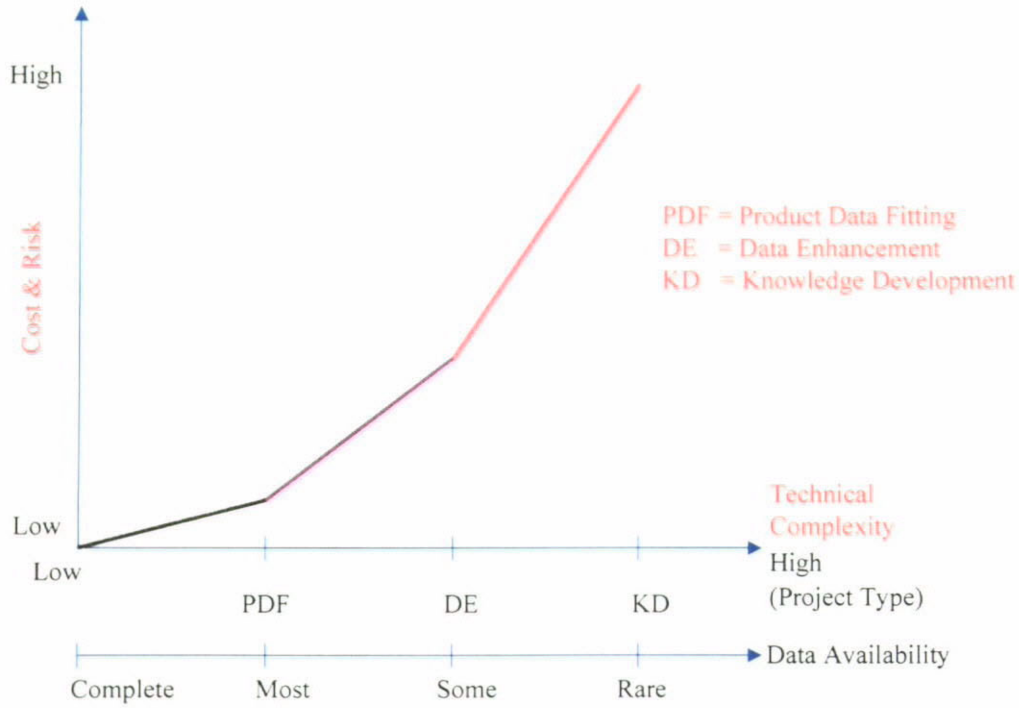


Fig. 12 Cost and Risk vs Technical Complexity and Data Availability

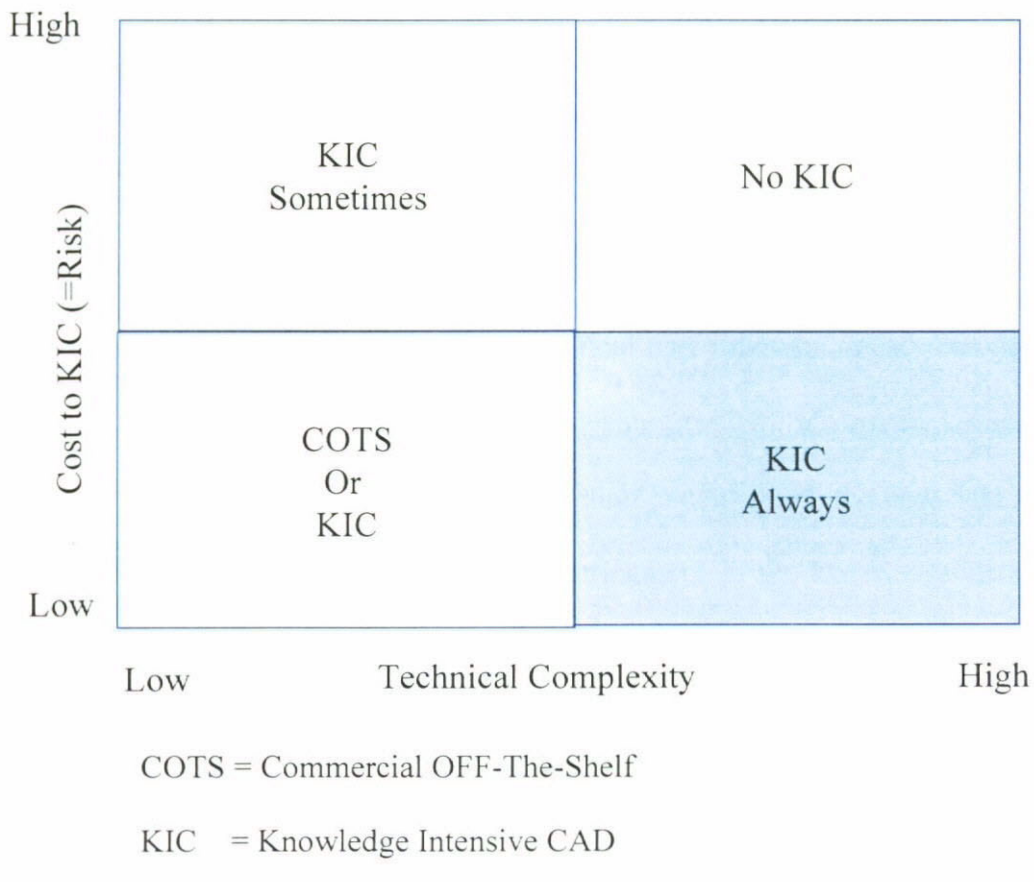


Fig. 13 Decision Matrix for a KIC Application

3.3 Workflow for the Development of a KIC System

The workflow for the development of a KIC system can be applied to any dedicated product design problem that needs to confine to a specific requirements. A process-driven approach was design to replace the experience dependent/estimation approach to appraise a new design alternative in a more effective way. The workflow for the development of a KIC system is shown in Fig 14. Basically, the workflow composes of two main phases that including knowledge crystallization and knowledge deployment. The knowledge crystallization focuses on the development of a knowledge database. The workflow guides a user to dissociate a problem into attributes of data type, nature of prediction and characteristics in such away that can act as filtering criterion for the recognition of the potential ANN algorithms for a KIC application development. For those ANN algorithms that process the required functionaries have been identified, all the ANN candidates have to undergo a training to find out the best performer. After the knowledge database has been crystallized from the legacy data sets, the knowledge deployment process that focused on the reuse of knowledge from the establishment knowledge database can begin. Through the development of a web-based graphical user interface, a user can deploy the KIC system to solve a similar or entirely new design problem in a particular application anywhere. Upon the completion of a new prediction is confirmed, the new data set result can then be input to the KIC system for the enrichment of the knowledge database for performance enhancement.

Once a decision of developing a KIC system has been made, the selection of the appropriate AI algorithms will come to play. Through the consideration of AI algorithm's generalization, flexibility, need of expertise knowledge and capability in handling design problem complexity, the potential candidates are sorted out. Generalization ability of a knowledge generation algorithm refers to the capability to adopt a new prediction based

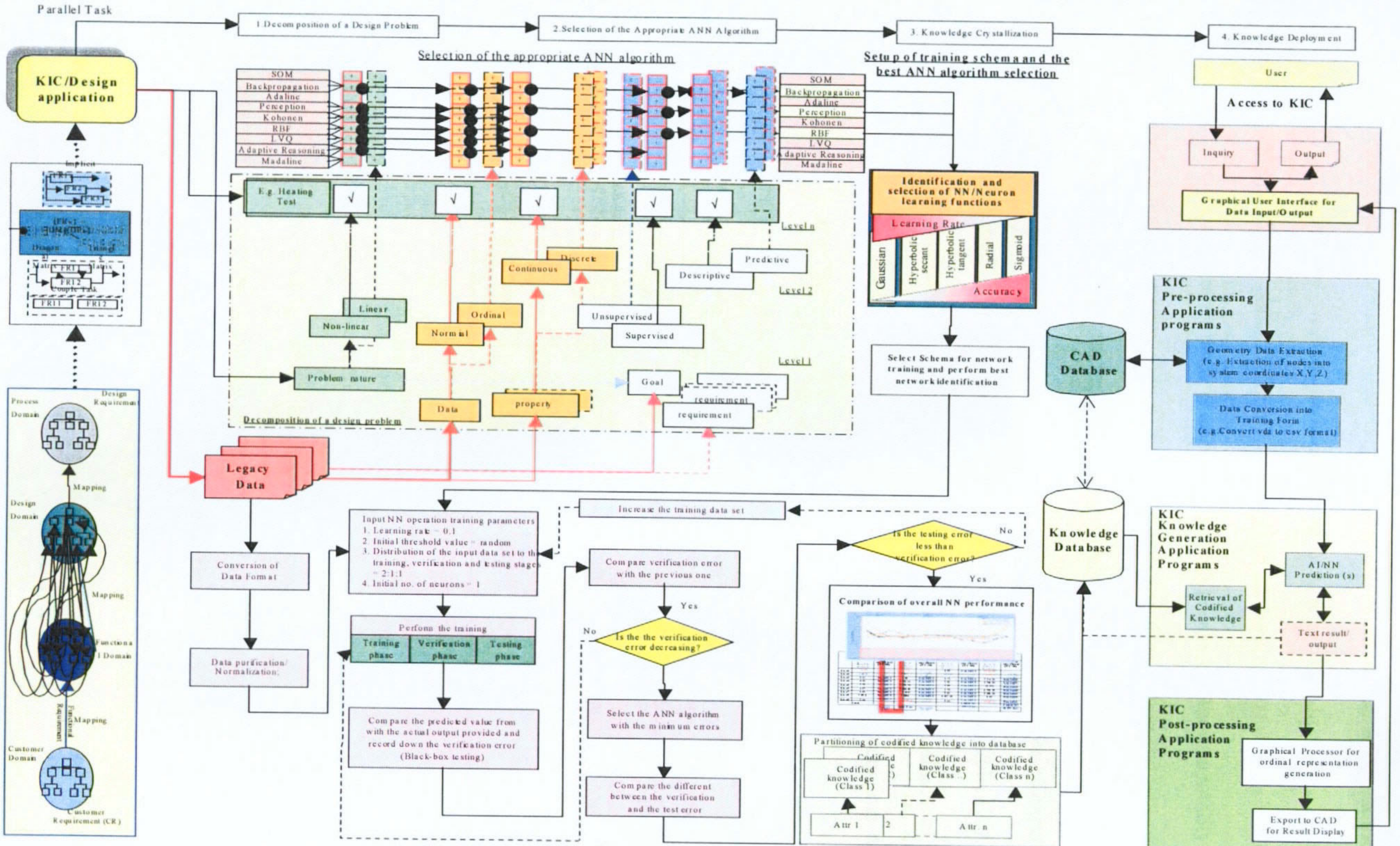


Fig. 14 Workflow for the Development of a KIC System

on the past data. If an algorithm claims its generalization ability is very high that means the tool will perform very well to predict/adapt to new situations. In case of a new product development, high generalization is preferred as adoption to many new situations is always required. On the other hand, if an algorithm with good generation capability but can only handle a few parameters, then its flexible can be regarded as low and will give a bias contribution towards the misfit. When the flexibility of an algorithm is high, decreases the bias error accordingly. Expertise knowledge means the degree of expertise that required for identify the problem definition and conducting the problem to the appropriate tool for analysis. The characteristics/problem handling capabilities of the most common used AI mechanisms for handling the above four area of concerns were summarized and listed in Table 3.

Table 3 Characteristics of AI Mechanisms

AI Mechanism / Characteristics	Neural Network	Rule Based System	Expert System	Case Based Reasoning	Fuzzy Logic
Generalization	High	Low	Low	Medium	Low
Flexibility	Medium	High	High	Medium	Low
Need of Expertisé Knowledge	High	Low	High	Medium	High
Capability in Handling Complex Design Problem	High	Low	Medium	Medium	Medium
Performance	3 High/ 1 Medium	1 High/ 3 Low	2 High/ 1 Medium/ 1 Low	4 Medium	1 High/ 1 Medium/ 2 Low

3.3.1 The Knowledge Crystallization Process

3.3.1.1 Data Collection and Conversion

The first step of the knowledge crystallization process concerns with the collection of legacy data sets and then the screening and purification processes. The third step is the conversion of the legacy data into a suitable format that can be input to ANN algorithms. Data will be classified into two types including: (i) structured (spreadsheets and report) and (ii) unstructured (image). For the preparation of the legacy data, usually represented/stored in textural file can be extracted and converted through a small conversion program. Searching criteria including subject name, geometry attribute with start indicator and end indicator can be input accordingly. Upon the completion of a search, the identified data fields can be stored into a CSV formatted file and then export for knowledge crystallization.

For a data set with unstructured format, data sets can only be extracted through the creation of a special extraction program. Since a legacy data set usually contain errors or incompleteness, therefore it is necessary to purify a data set by filtering out all these incorrectness.

The following three ways are suggested for the purification of a data set:

(i) *Normalization* - Improves the accuracy and efficiently of a neural network algorithm involving distance measurement.

(ii) *Reduction* - Data size can be reduced by aggregating, eliminating redundant features, or clustering.

(iii) *Integration* - Data sets from multiple sources can be merged into a coherent data store, such as a data warehouse or a data cube.

In addition, when data sets are insufficient, additional data sets have to supplement by new experiments (Fig. 15). Through the use of above methods, data with error derivations that greater than a particular tolerance can be eliminated whilst the possible errors inducted by the raw data sets can also be minimized. Once a set of legacy data has been purified and a number of potential ANN algorithms have been identified, the selection of the best ANN candidate can then be started. The training will be stopped base upon the result of converging process limits whilst the best ANN algorithm can then be identified.

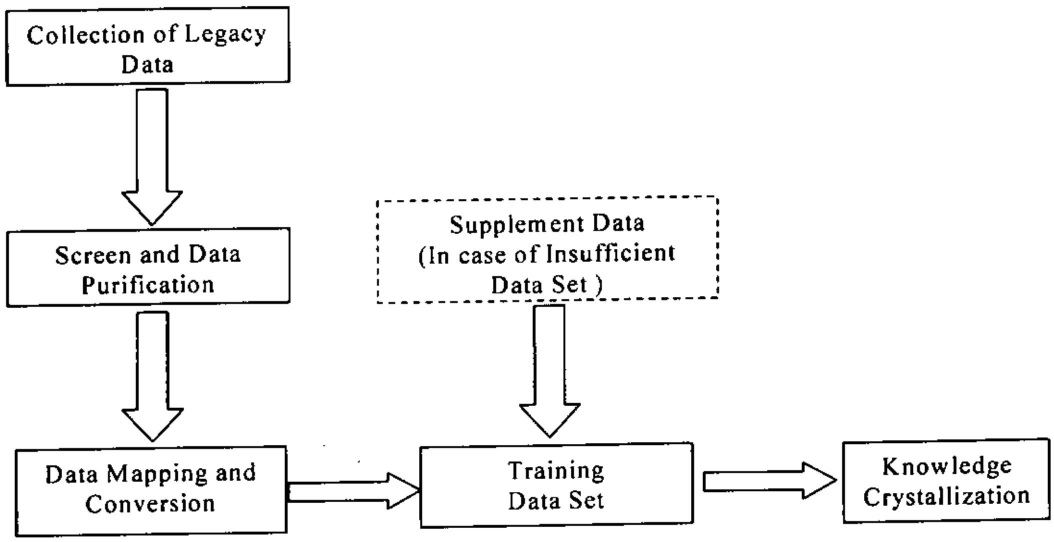


Fig. 15 Capturing of Legacy Data

3.3.1.2 Selection of ANN Algorithm

Once the critical concerns of a design problem, its data and prediction natures have been identified, the selection process of the ANN algorithm can be started. Each ANN algorithm has its own prediction handling capability. Therefore, the primary ANN algorithms candidates have to be sorted out through the mapping of problem nature, data type, date property, study goal and the study requirements. For example, in a heating test, attributes of data sets can be classified into nominal with continuous property, the outcome requirement is predictive and then the goal of the study is supervised. Nominal data type means the data is a numerical representation (e.g. spreadsheet data) while ordinal data is classified as image, characters and etc. Descriptive means the use of data mining is to discovering the patterns, associations and clusters of the information while predictive is to make use of those patterns to predict future trends and behaviors. Supervised means a design task consists of result data for the learning process while unsupervised means the design task does not contain any result data for the learning process. Once the nature of a design problem and its data type have been disassociated into element of concerns, capable ANN algorithms can be identified through a simple mapping process. Problem nature of a heating test can be classified as a non-linear in nature and its requirement predictive, whilst the expected thermal distribution as a prediction within continuous behaviors with and an expected goal of supervised.

In most cases, there exist several ANN algorithms that can satisfy all the primary requirements to solve a specific design problem. The most common available ANN mechanisms including: Self-Organize Mapping (SOM), Backpropagation (BP), Adaline, Perception, Kohonen, Radial Based Feedforward Neural Network (RBF), Madaline, Learning Vector Quantization (LVQ), Adaptive Resonance Theory (ART) were list in Fig. 16. Each algorithm has its own characteristic. For example, SOM can handle problems of non-linear type, both nominal and ordinal data sets, discrete data property, unsupervised study goal and descriptive study requirement.

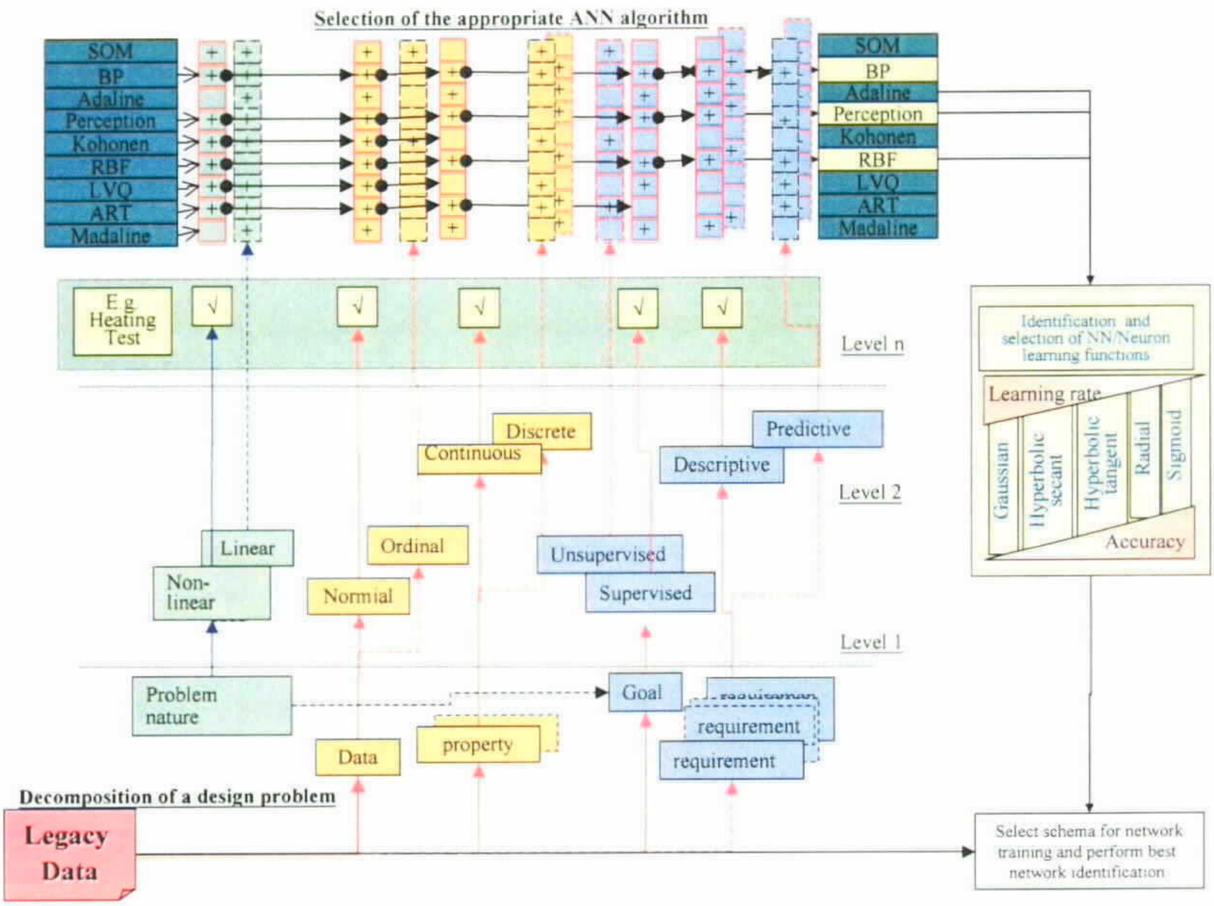


Fig. 16 Model for the Problem Decomposition and Appropriate ANN Algorithms Selection

3.3.1.3 Setup of Training Schema and the Identification of the Best ANN Algorithm

After the recognition of these potential ANN algorithm candidates, it is necessary to let then all go through the knowledge crystallization process before the best ANN algorithm can be identified. The training of the data sets is of critical importance in a knowledge crystallization process. The number of data sets that require for properly train a neural network suggested by Barens [1998]. Through a series of training, errors and convergences of each ANN algorithm are found and their performances compared. The ANN algorithm with the smallest errors and quickest convergence will be the best and be selected to solve the particular type design problem. Since each ANN algorithm has its own network structure and typical requires different number of neurons with different weightings to represent a design phenomenon, it is necessary to setup a proper training schema to control the learning rate and obtain the performance indications. In case of the selection of the activation function, if the complexity of the problem is high, just in case a multi-discipline non-linear type, the time that requires for training will be a very significant issue. The "Guassian" approach that process with the highest learning rate will be selected. In the reverse case, if the training time is not a critical concern, "Sigmoid" approach that gives the highest accuracy shall be used as the learning function. Therefore, a compromise has to be made in between both learning rate and network size in order to develop an efficient and cost effective training scheme for a predefined requirement of accuracy. As a trade off, based on the limitation of computational time, amount of input variables and their properties, a suitable training scheme has to be formulated before the training of the selected neural network algorithms can be started.

The development of a neural network prediction consists of three phases that include: (i) training, (ii) verification and (iii) testing phases. In the training phases, training parameters including: learning rate, threshold value (weights of neurons) and parameters for the validation and testing of the network have to determine. A learning rate can be set to high or low while the initial values of the threshold value should be set as random.

As the number of neurons and layers and the initial conditions will determine time of training, the settings of these parameters are very important, however, there does not exists any systematic way to set these values and normally, this process can only be done in a trail and error base. According to the proposed model, training should be started with lower learning rate and randomized weights. Several iterations will be required before an increase of neuron number of the hidden layer. The input data that need to be distributed to the training, verification and testing stages of a data set should be in a ratio of 2:1:1 [John Petkov].

Once training has been completed, the corresponding verification has to be taken place. The output/prediction of the data set has to compare with the actual result with a test that known as the "black-box testing". In a normal case, the verification errors will drop progressively as the training is carried on. In case, the verification error starts to rebound during the verification process, the ANN algorithm has over-learnt (i.e. the data is overfitted). Under such circumstance, a system developer has to stop the training process and restore the system back to the previous status with the least verification error.

After the completion of the verification, the testing phase can then be started to evaluate the performance of the selected ANN algorithm through the use of derived weights. The derived weights are obtained by measuring the ability of the ANN algorithm to predict. The black box testing comparison of testing results to historical results is again applied to appraise whether the system can produce. Even through the testing error can provide a final check of the overall performance of an ANN algorithm, the deviation of the verification and the testing errors also closed monitored. In case a neural network give a significantly large testing error than its verification error, the neural network needs more cases (increase the training data set or increase the network complexity) because a very low verification error might be obtained by chance. In contrast, if the value of the verification and testing error are both very close together, the network system can be regarded as learned to generalize reliably. The above procedures have to be repeated and applied until the best ANN algorithms can be identified. At the end, the ANN algorithm that can meet both the certainly level of accuracy with the lowest error in verification, testing and the deviation between those errors will be the final ANN algorithm that fits the design application. Before casting of a codified knowledge database into a multi-KIC system, the storage and partitioning must be carefully considered and designed, because these issues will affect the further development of further applications. The detail workflow for the knowledge crystallization process is shown in Fig. 17.

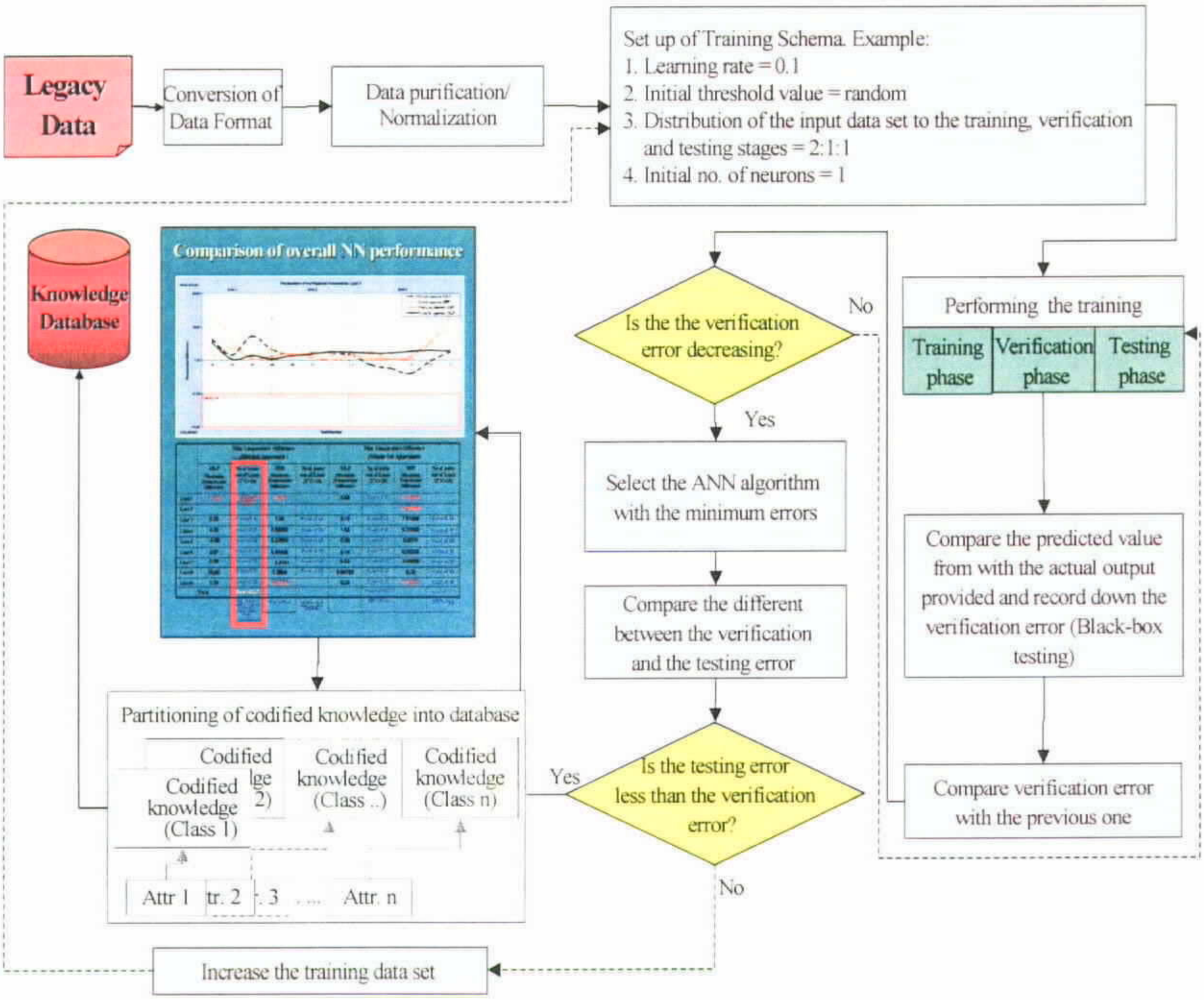


Fig. 17 Workflow of Network Training and Best Network Identification

3.3.2 *The Knowledge Deployment Process*

Once the codified knowledge database has been established, it can then be used to answer/entertain a new design enquiry through a knowledge deployment process. The workflow of the knowledge deployment process is shown in Fig. 18. The process composed of two steps: (i) the development of a graphical user interface for an user's inquiry and visualization of a KIC output/prediction, and (ii) the development of knowledge application programs for data input, conversion, retrieval of codified knowledge and the output of a KIC prediction system.

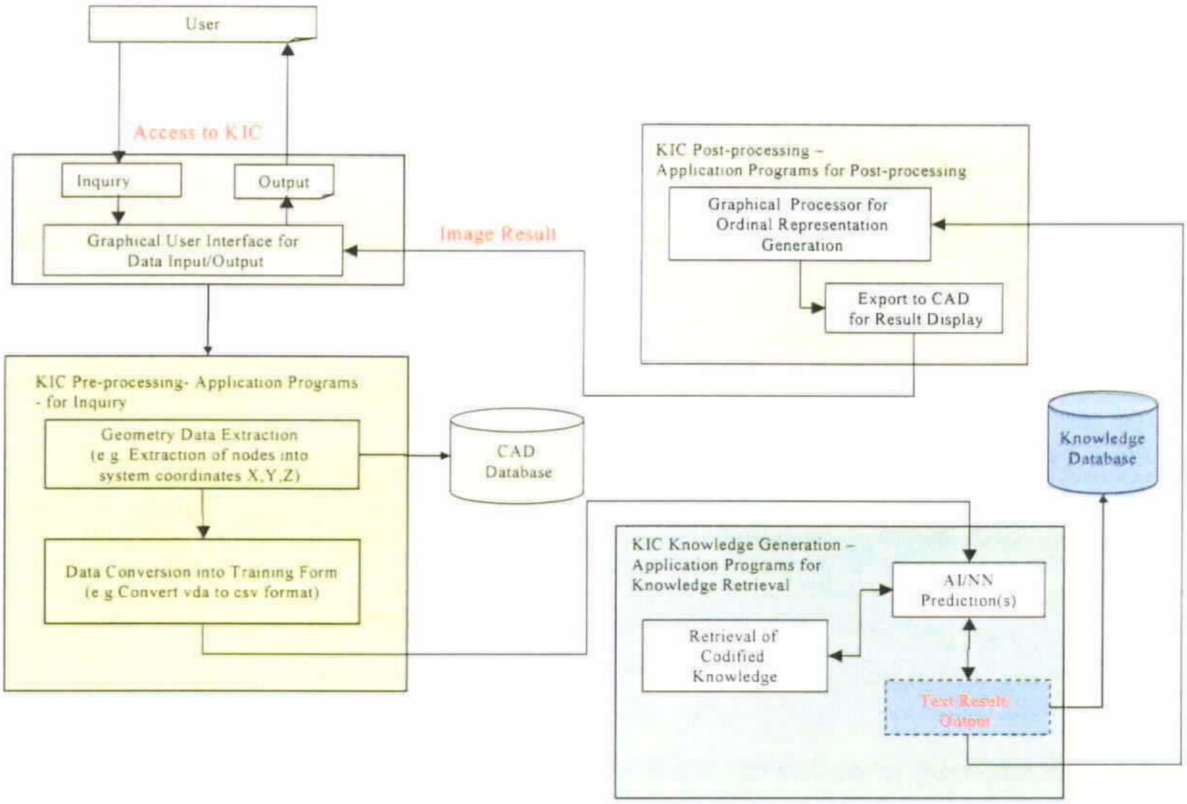


Fig. 18 Workflow of the Knowledge Deployment Process

3.3.2.1 Developing of the Pre-Processing Application Programs for Inquiry

To start with a knowledge deployment process, a new enquiry has to be input in the first placed through a web-centric graphical user interface. The raw data/design style has to be input to the KIC system and an application program has to be developed for data recognition. Input data after the recognition process needs to be converted to an appropriate data format that can be recognized by the KIC system. For example, a user can input a 3D model for inquiry. In order to permit such recognition, in ease of the heating test, an automatic slicing system has to be developed to slicing the input 3D geometry into nodes whilst the corresponding coordinates (x, y and z) can be detected.

3.3.2.2 Design of the KIC System Architecture

The design of the KIC system architecture depends upon development of the degrees of service and automation intended for the service provided. The key issues of concern including the creation and management of (i) the graphical user interface, (ii) the function model, and (iii) the domain model. The levels of service and functionalities in the application programs and program interface levels are shown in Fig. 19.

(i) The Domain Model Management

The domain model management relates to the performance of the execution or an inquiry command activities. The domain management controls the activities that include: (i) data extraction, (ii) knowledge deployment, (iii) data embedment knowledge, and (iv) result displays.

(ii) The GUI Management

The GUI management concerns with the development of an interface for support the input and output. GUI actuates operation command (s) from a user and provides functions including: opening, execution, delete, modify object data and display of prediction of an enquiry.

(iii) The Function Model

The management of function model includes the execution of an inquiry and provides the required functions for the knowledge deployment and tapping of knowledge from the knowledge database of the KIC system. Furthermore, the system and the graphical user interface are suggested to build on Web so that a user can assess the system through a Web-browser in any where with a plug-in program to perform a request through the Internet.

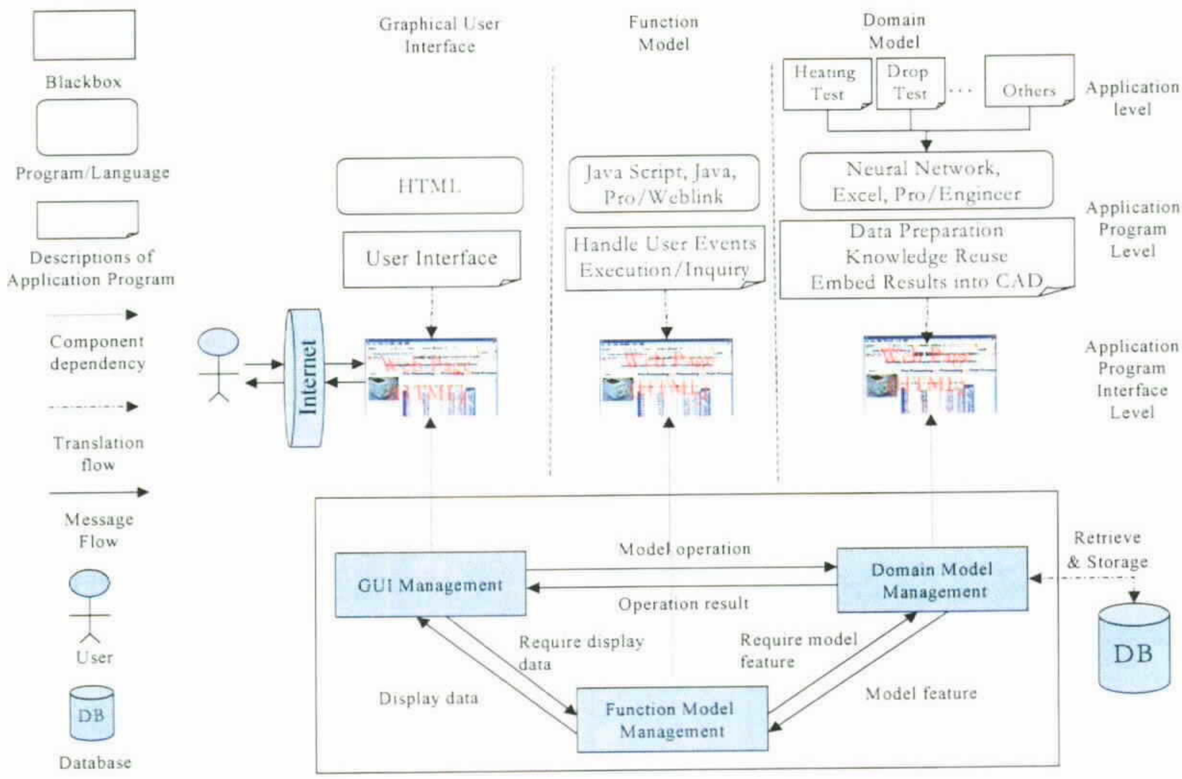


Fig. 19 The Architecture of the Proposed KIC System

3.3.2.3 Development of the Post-processing KIC Graphical User Interface

The last step in the KIC development process is to construct a post-processing application program for the displacement of the intended result when the prediction of a KIC application is transferred for further CAE analysis. For example, in the heating test, after the prediction of the surface temperature of a new plastic toaster case design, the resultant temperature/thermal strain that predicted is required to display for visualization.

Chapter 4 Case Study – Application of KIC for the Prediction of Thermal Displacement of a Plastic Toaster Case

4.1 Background of Study

In the small electrical family appliance industry, housings of a toaster, iron, hair dryer, water jug have a common design concern that is the thermal strain/displacement when they are in operation. Such design problem has to be solved by multi-discipline theories whilst the structural properties of the plastic casing materials are non-linear. For the calculation of the thermal strain of a plastic toaster case, it involves five multi-discipline and non-linear considerations (Fig. 20) that include (i) convection, (ii) conduction, radiation (iii) non-linear stress-strain, and (iv) air flow under operation.

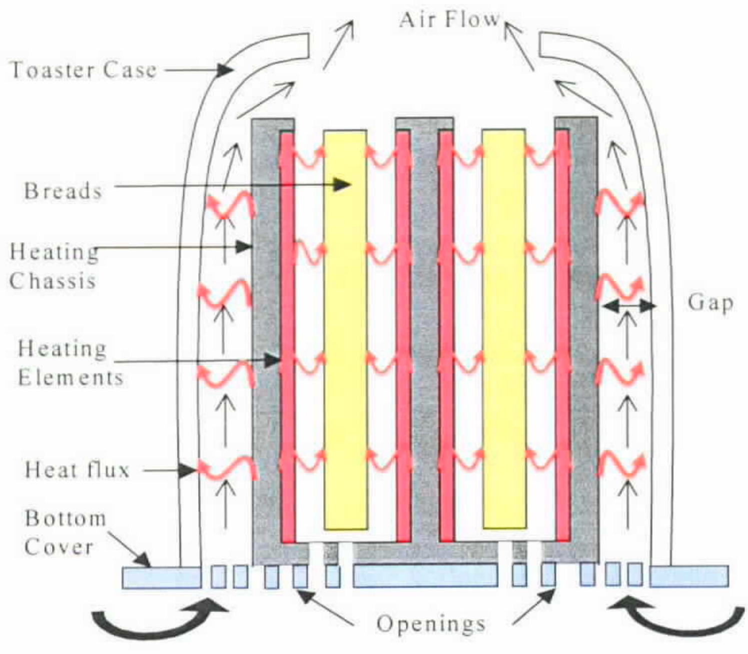
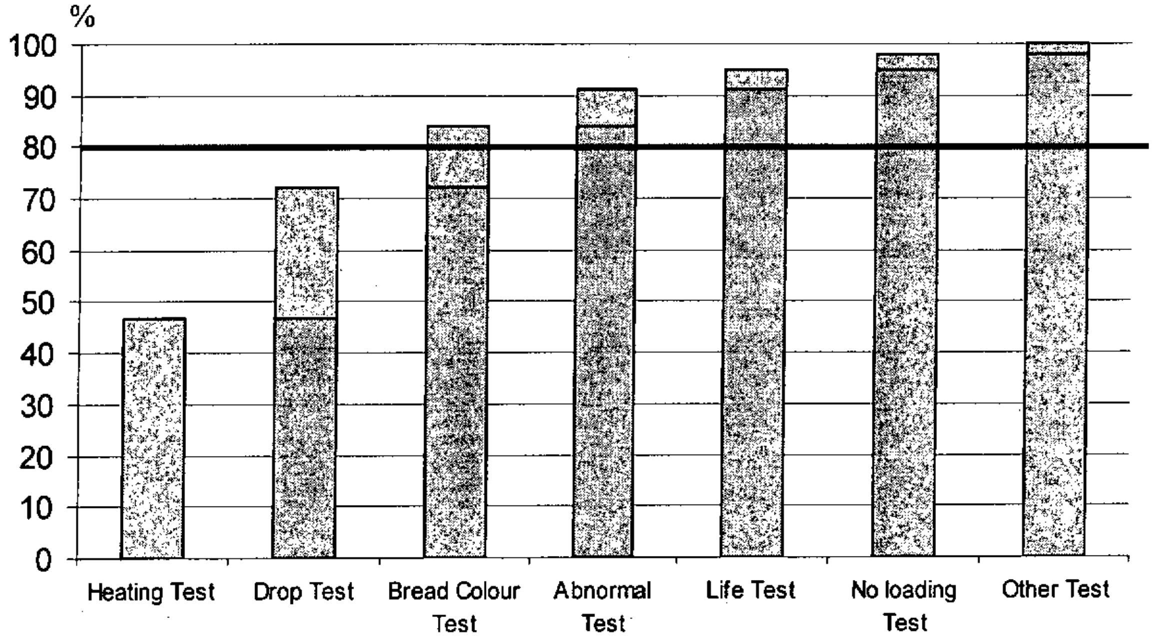


Fig. 20 Schematic of a Toaster Heating Test

When a toaster case is in operation, the principle heating processing is done through the convection and conduction whilst the secondary heating is through radiation. When the air in between the openings is heated up, a stream of airflow will start to circulate that will interrupt the heating flux. According to the final temperature gradient profile, a plastic toaster case will be expanded according to its non-linear stress/strain behavior. Such type of design problem is classified as non-linear and multi-discipline as nature by Kristopher Seluga [1998]. At the moment, almost all companies in the industry are still using physical prototypes and the trial and error approach to find solution or deal with such problem.

4.2 Assessment/Justification for the Set Up of KIC Heating Test

In the past two years, the partnered company G.E.W was forced to trim its product introduction time for a new toaster model from six to twelve months down to three to four months but over 60% toaster projects could not meet the deadline of schedules. According to a Pareto analysis (Fig. 21) in the causes of delay in 2002, it was found that three functional tests that including heating, drop and bread color were accounted for over 80% of failures and caused the delays. However, the company is still relying on her individual designer's capability and the trial and error approach. The worst case of delay was up to nine months. From the pie chart shown in Fig. 22, one can find that, the toaster business accounts for 60% of G.E.W's business and the number of new toaster project that requires to develop had been increased from 25% to 48% (approximately double) in five years times (Fig. 23). Even through the development of toaster has been practiced for many years, the successful rate of the products that can pass a new heating test had suddenly decreased by 42% because of the increasing complexity of cosmetic or styling. With the new requirements of the market, the experience that cumulated from the past can no more apply to solve such change in industrial designs. Huge amounts of physical prototypes were built in the conceptual design phase to test the feasibility of the design alternatives. The average fabrication time of a physical prototype by RP is around three days for one new design, and normally one extra prototype will be needed for final confirmation. The cost of building the physical prototypes were over \$2,400,000 (\$25000 x 48 x 2) in the year whilst the time required for a complete heating test takes 24 days.



Remark: Other tests including bread carriage test, impact test, screw test, pull test, pull test and creepage test

Fig. 21 Pareto Analysis of Toaster Functional Test

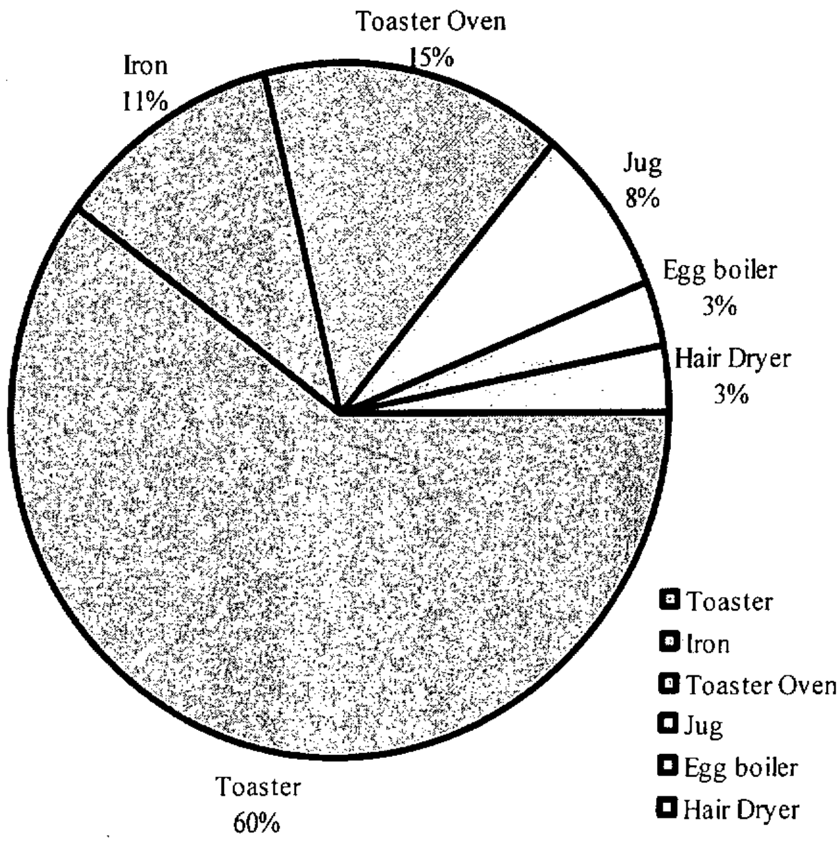


Fig. 22 Business Distribution of G.E.W

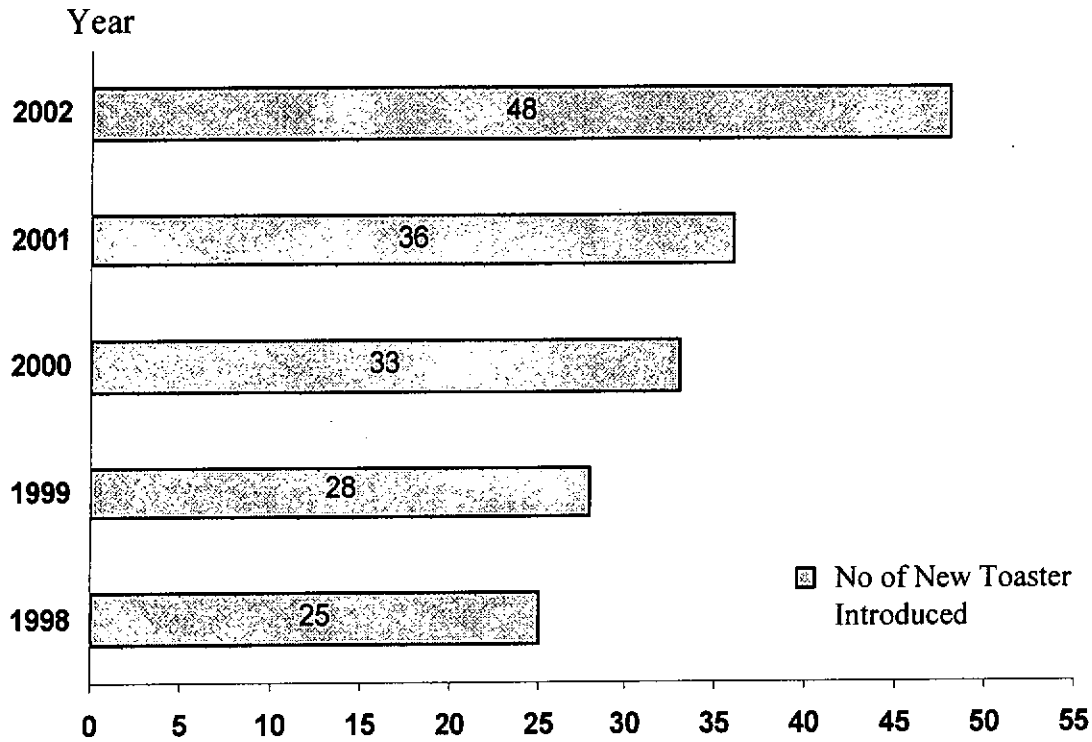


Fig. 23 Number of New Model Introduced

The company had tried to make use the entirely computer aided engineering approach. However, at least three different CAE software packages have to be used to solve such kind of multi-discipline/ non-linear case design problem (Fig. 24). As the general confidence of a CAE software package prediction usually ranged from 60% to 90%, the accumulated accuracy of the use of three consecutive CAE package, with an average 80% accuracy, will drop to around 51% (0.8x0.8x0.8). Furthermore, the investment of softwares, resource, staffing and time to run such virtual experiments would be tremendously large and long. Therefore, before the entirely CAE/FEM/FEA approach becomes practical, the use of KIC to address a design problem of multi-discipline/non-linear with plenty of legacy data sets is desirable.

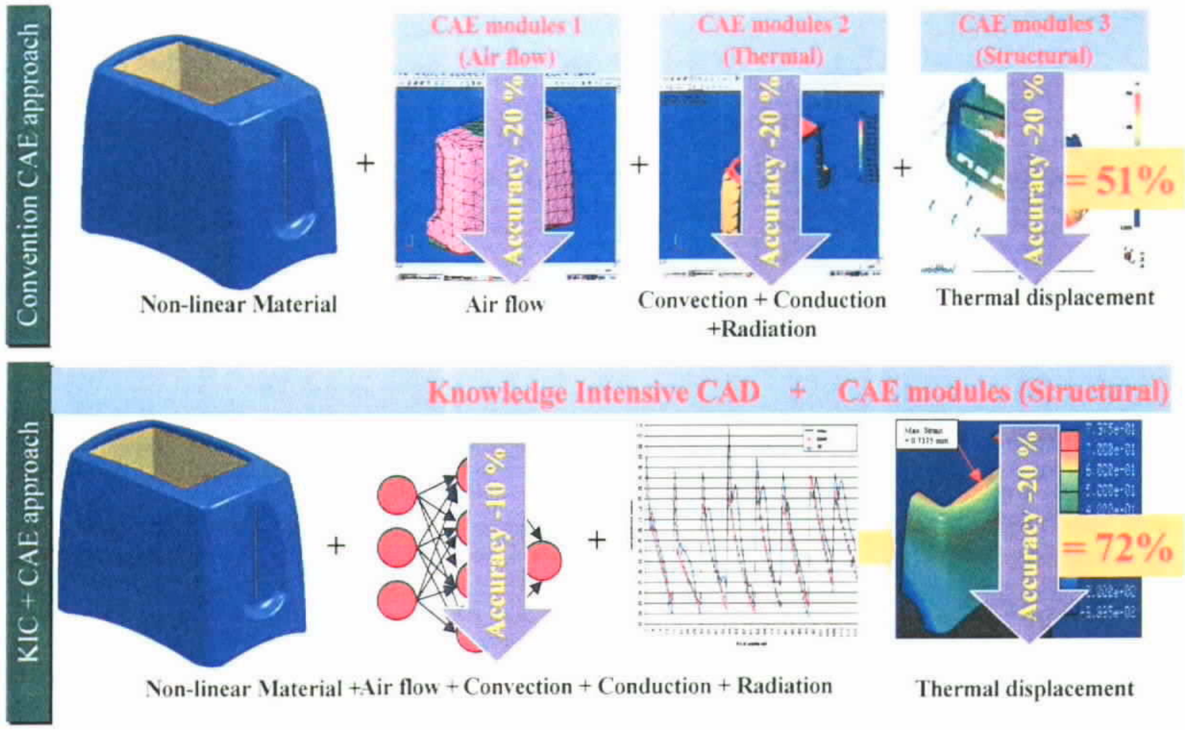


Fig. 24 Accuracy of Using Convention CAE Approach and Proposed KIC Approach

4.3 The IEC Heating Test

According to IEC-CEI 335-3-9, the power setting of a toaster in a heat test has to be set 1.15 times of its maximum defined value. With bread(s) inside, the toaster is heated up and set to normal operation. When the bread color becomes golden, the toaster is deactivated and allowed to cool down for 30 seconds with a fan. The process is repeated for a period of 20 minutes and the maximum toaster case temperature should not exceed 130°C. Other than the thermal effects of the heating, airflow in openings, non-linear plastic behavior, the release of frozen in stress during the injection molding stage will come to play and the plastic case dimensions will be variant.

4.4 Set Up of the KIC Investigations for the Heating Test

Two investigations had been formulated to evident of the effectiveness and suitability of the proposed methodology. These included: (i) prediction of a dedicated model with variable sizes, and (ii) prediction for an entirely new toaster case design from previous design toaster cases. Six toaster's designs with different shapes were selected for the investigations (Fig. 25). Four toaster's designs were chosen for data training set and each case design with four layers that included +0(normal), +2mm, +4mm and -2mm while the rest whilst the rest two for confirmation.

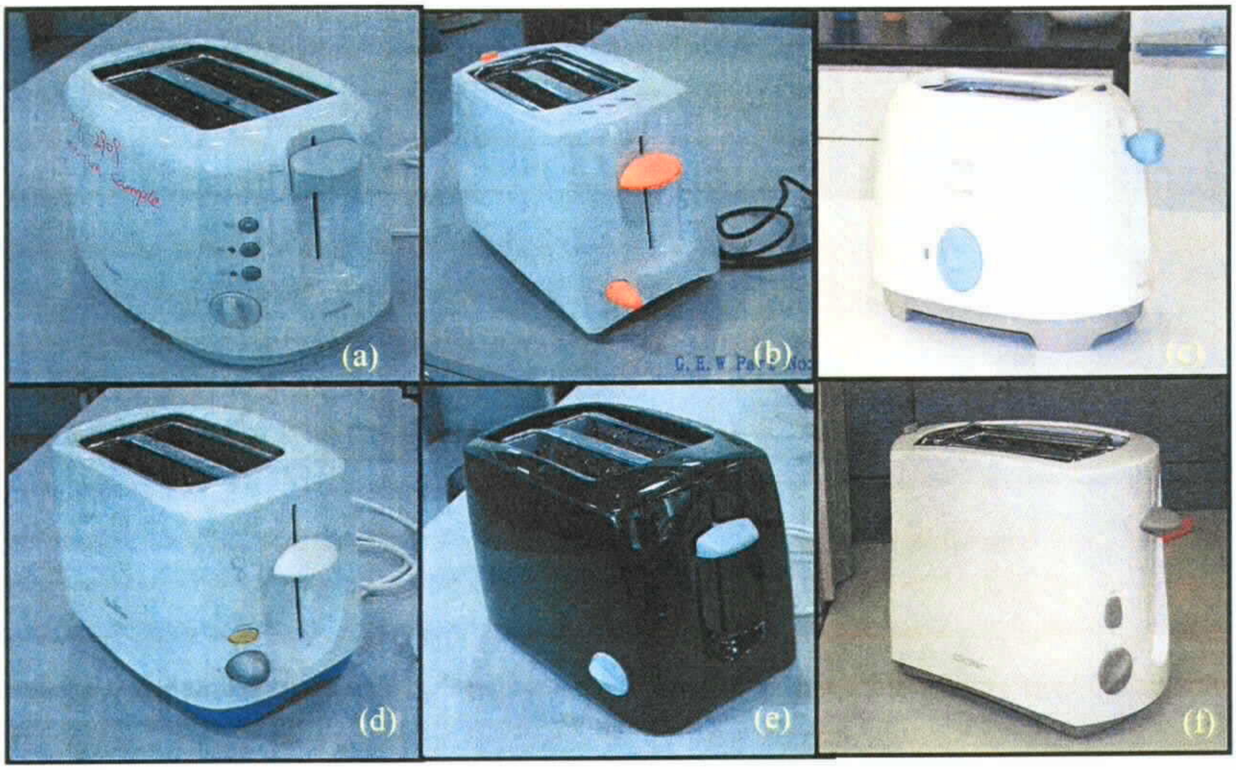


Fig. 25 Six Toaster Models are Selected for Investigation

As the toaster case is symmetry, therefore, only a half-model was used for the investigations and each model were divided into eight regions by nine line segments (Fig.26) with thirteen layers to intersect the nodes for temperature record and thermal strain displacement. Therefore, each set of training data contained 9 x 13 x 4 = 468 nodes and the total number of training data for the four models was 1,872 nodes.

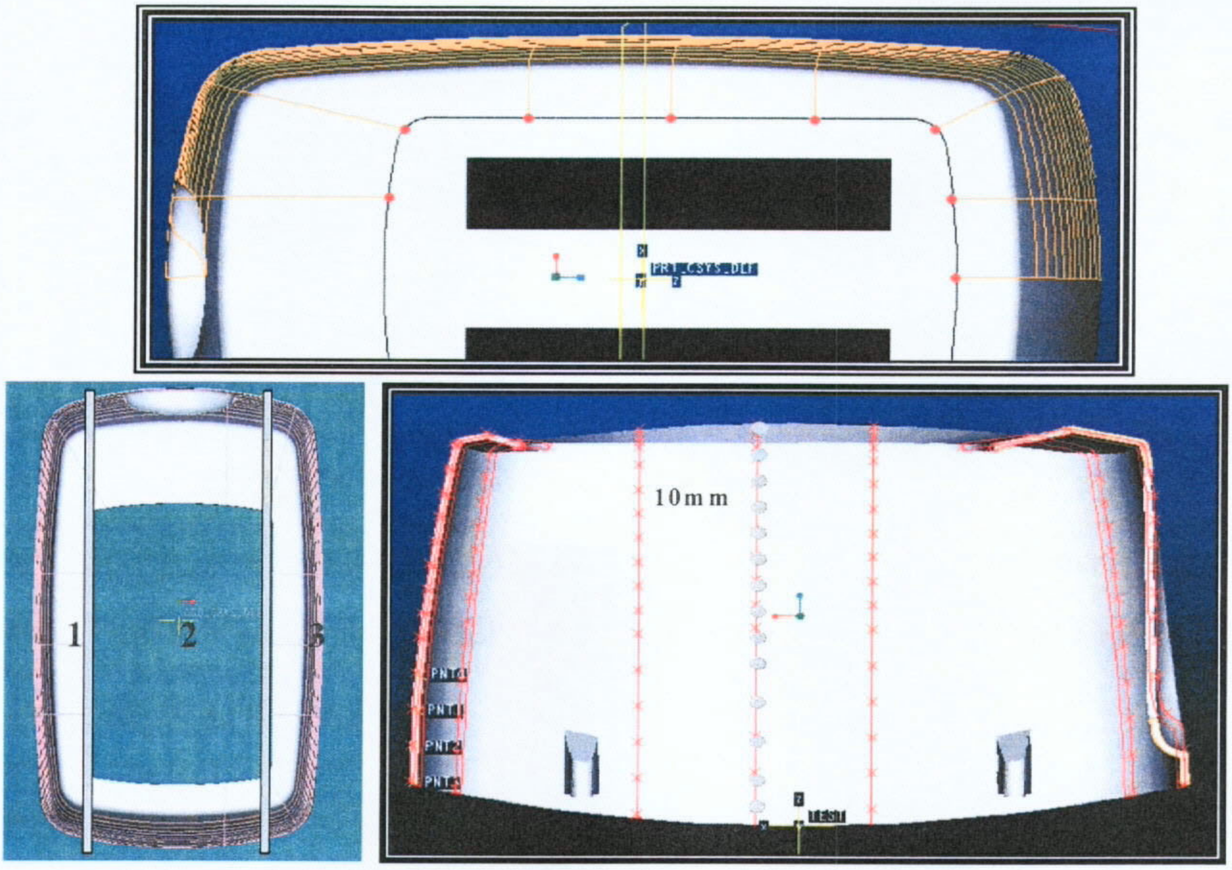
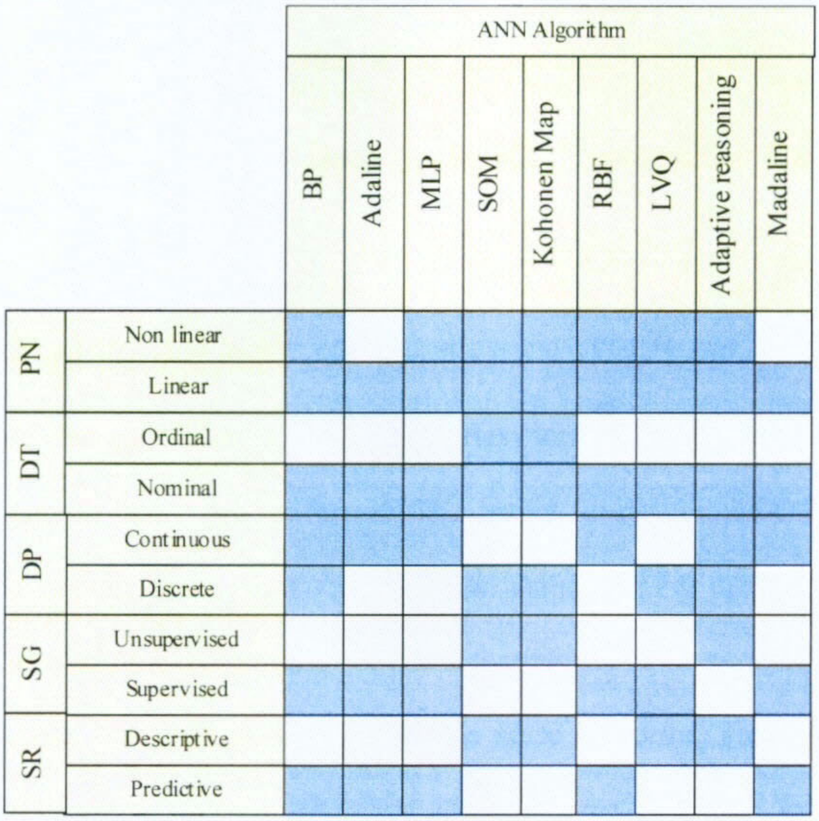


Fig. 26 Partitioning of the Toaster Case for Temperature Input

4.5 Disassociation of Problem Attributes and Properties

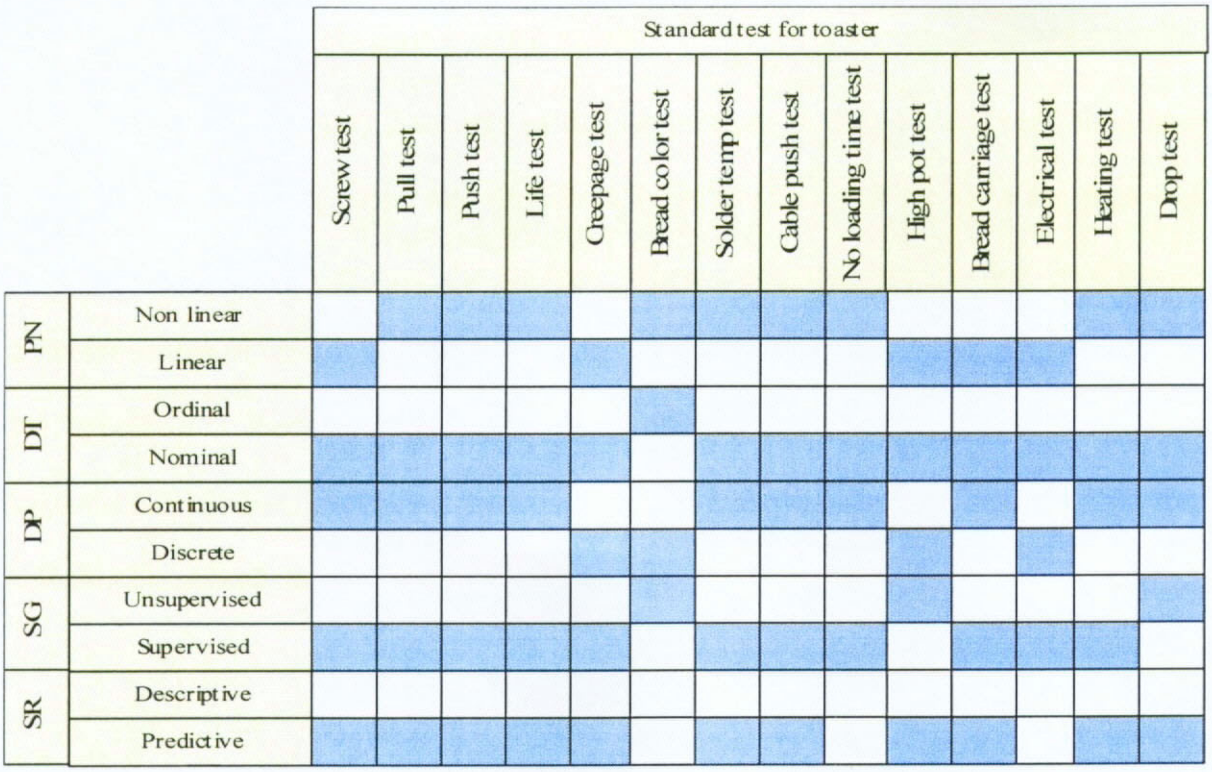
The first step to tackle the heating test problem was to examine the nature and characteristic of its attributes/elements critically. The problem characteristic and data type were dissociated and grouped into classes that required for mapping the appropriate ANN algorithms in the following stage. Selection of the correct or the most preferable algorithms for a design task is critical and will highly affect the knowledge crystallization process and the subsequent building of the knowledge to database. The selection of the possible ANN algorithms were done according to the decision table mentioned in the previous chapter whilst the attributes were decomposed such as problem nature, data type, data property, study goal, and task requirement (Fig. 27).

In the heating test, the prime input data was the geometry coordinates that represent a specific shape and temperature in numerical format, therefore the use of ANN algorithm was sufficient to handle such continual data property and nominal data. All the available or assessable ANN algorithms that process such capability of handling both the data and problem property and the data type were listed out. Fig. 28 showed the decision matrix. Through the mapping of the problem nature (PN), data property (DP), data type (DT), study goal (SG), and task requirement (TR), to the handling capability of the ANN algorithms, three ANN algorithms that included (i) backpropagation (BP), (ii) multi-layer perceptron (MLP) and (iii) radial basis feedforward (RBF) were sorted out and would be the potential candidates for final ANN selection. However, due to the resource and availability limitation, only the MLP and RBF algorithms were selected to undergo the knowledge crystallization process.



PN -Problem Nature, DT - Data Type, DP -Data Property, SG - Study Goal, SR - Study Requirement

Fig. 27 Decision Matrix of the Selection of ANN Algorithms



PN -Problem Nature, DT - Data Type, DP -Data Property, SG - Study Goal, SR - Study Requirement

Fig. 28 Decomposition of the Toaster Design Problems

4.6 Conversion of Legacy Data to the KIC System for Knowledge Training

In order to sort out the best ANN algorithm for the KIC for heating test, all geometry legacy data sets (the coordinate of case geometries) were input to the system through a visual basic program into a pre-set format. The output format for the CAD system was vda format that include curve, point attributes, user name, etc. For the ANN prediction, it was required to collect the toaster case point sets that represent the geometry behaviors. A visual basic system was built to filter out all the noise and error. Then, the data in vda format was transformed and converted into a csv format (Fig. 29) for further ANN analysis.

4.7 Data Analysis and Purification

Fig. 30 showed the legacy data sets of the temperature profile for different sizes and styles of toasters. It was found that the different size of cases with the same shape gave a similar profile of temperature distribution. When comparing the heating profiles of different shapes of case, it was found that their profiles were quite similar. Any error (Fig. 31) appeared in the smoothing process was cleaned and purified so that noise and inconsistency data set would not be existed. Fig. 32 shows a heating data set after the process of purification.

4.8 Investigation I- Prediction of Dedicated Style with Variable Sizes

The first investigation was aimed to find out the capability of ANN in predicting the temperature profile of a new toaster case with a dedicated geometry but with different sizes. In this case, the data sets of four different sizes of a dedicated toaster case and their temperature profiles were put into training. The sizes of the cases including one nominal (+0mm), one under size (-2mm) and two oversizes (+2mm and +4mm) were input for the training and the establishment of a knowledge database whilst the toaster case with size +3mm over size was used for the knowledge prediction. The tolerance acceptance (difference between the predicted temperature and the actual temperature) of a prediction should not exceed +20 or -10°C.

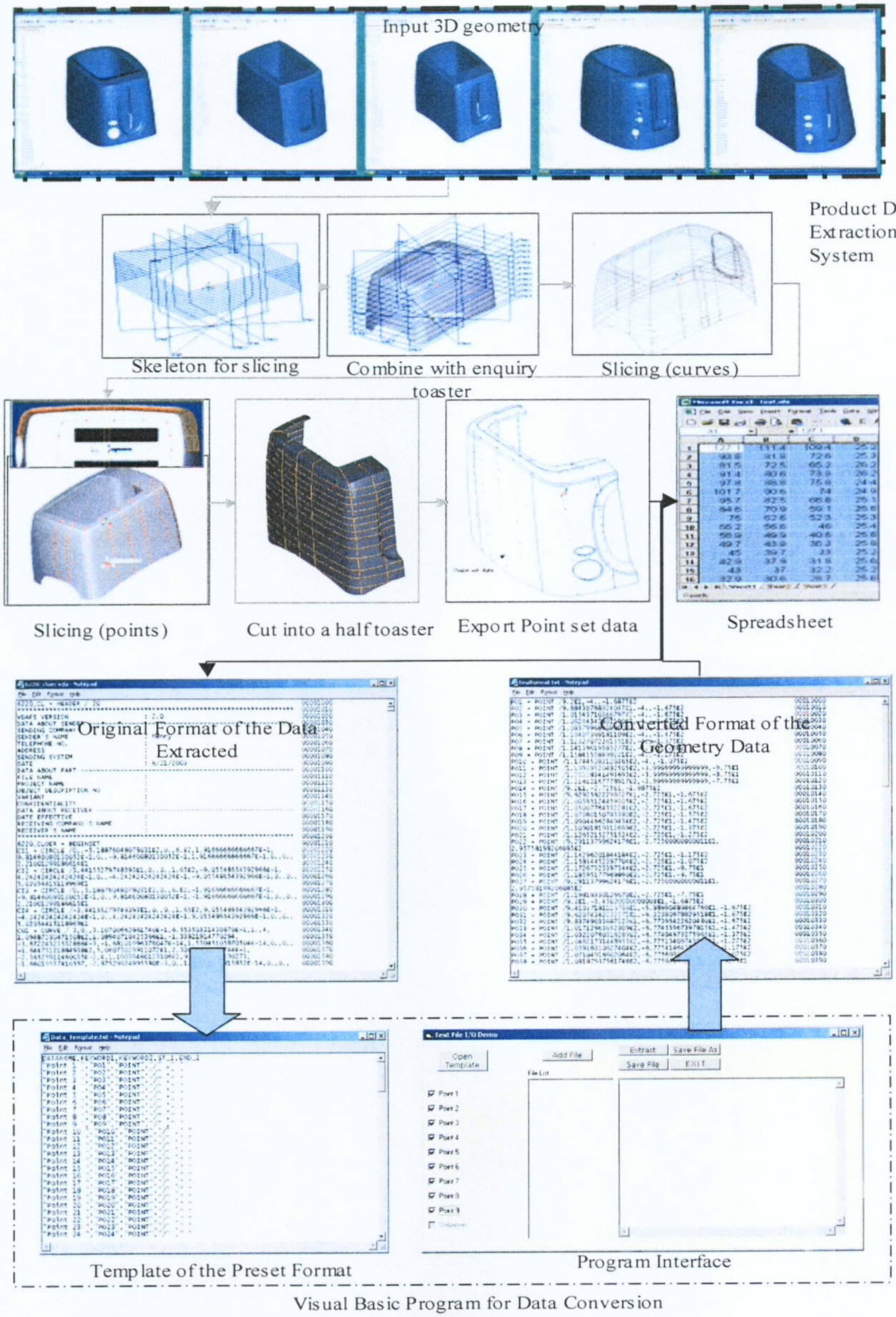


Fig. 29 Recognition and Conversion Process for a 3D Geometry

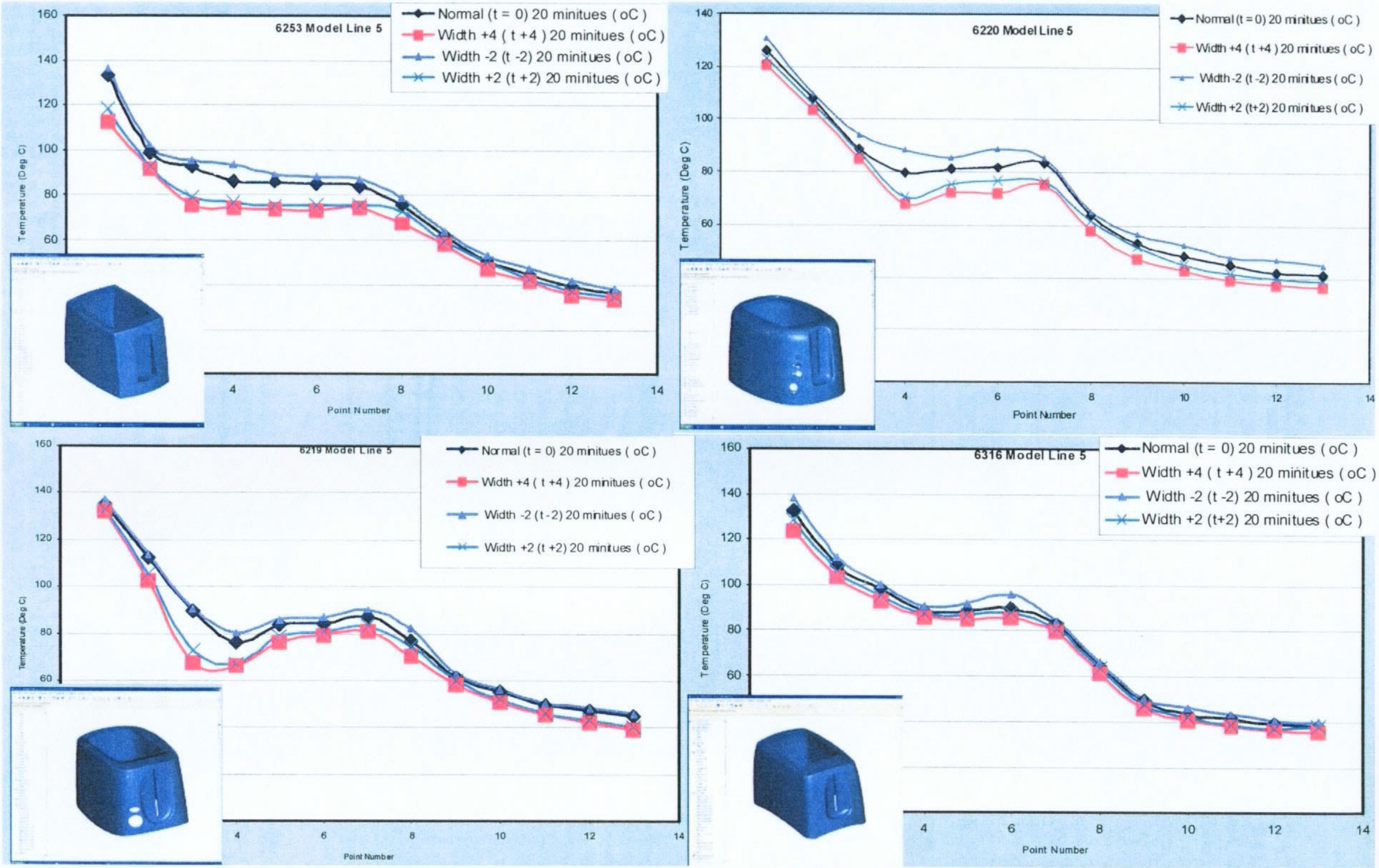


Fig. 30 Experimental Results of the Heating Profile for Different Size and Shape of Cases

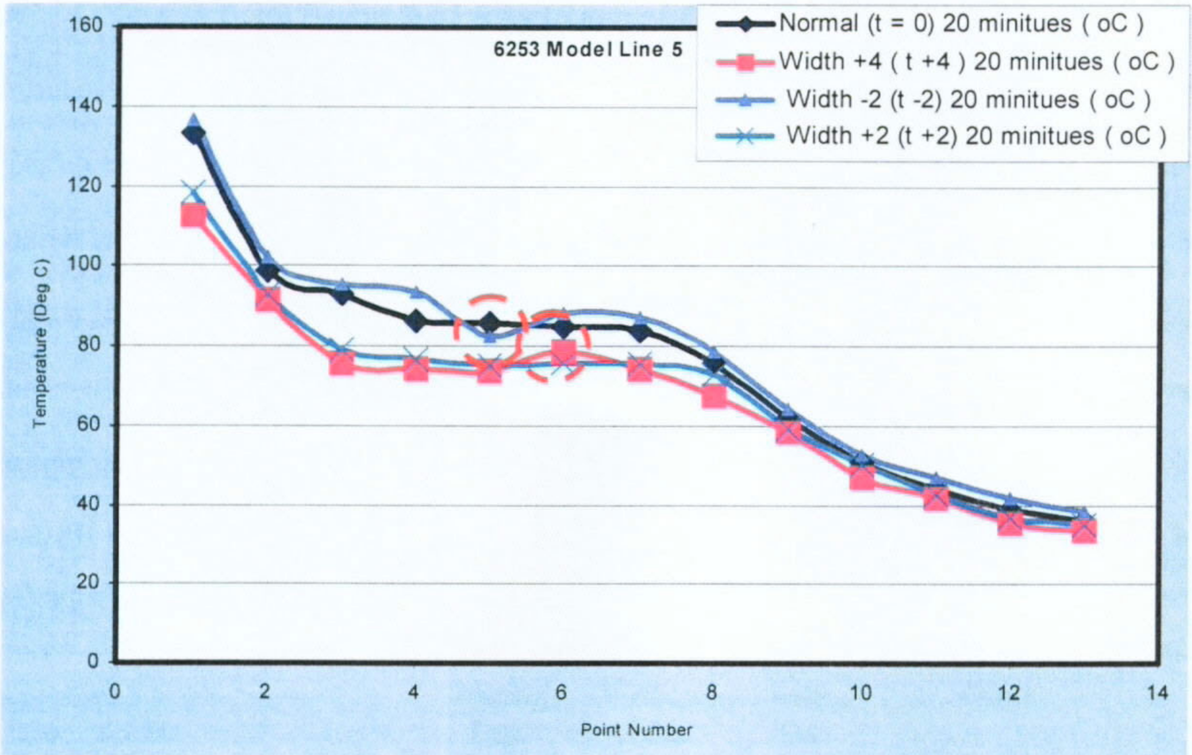


Fig. 31 Raw Data Set for the Toaster in Line 1 Location

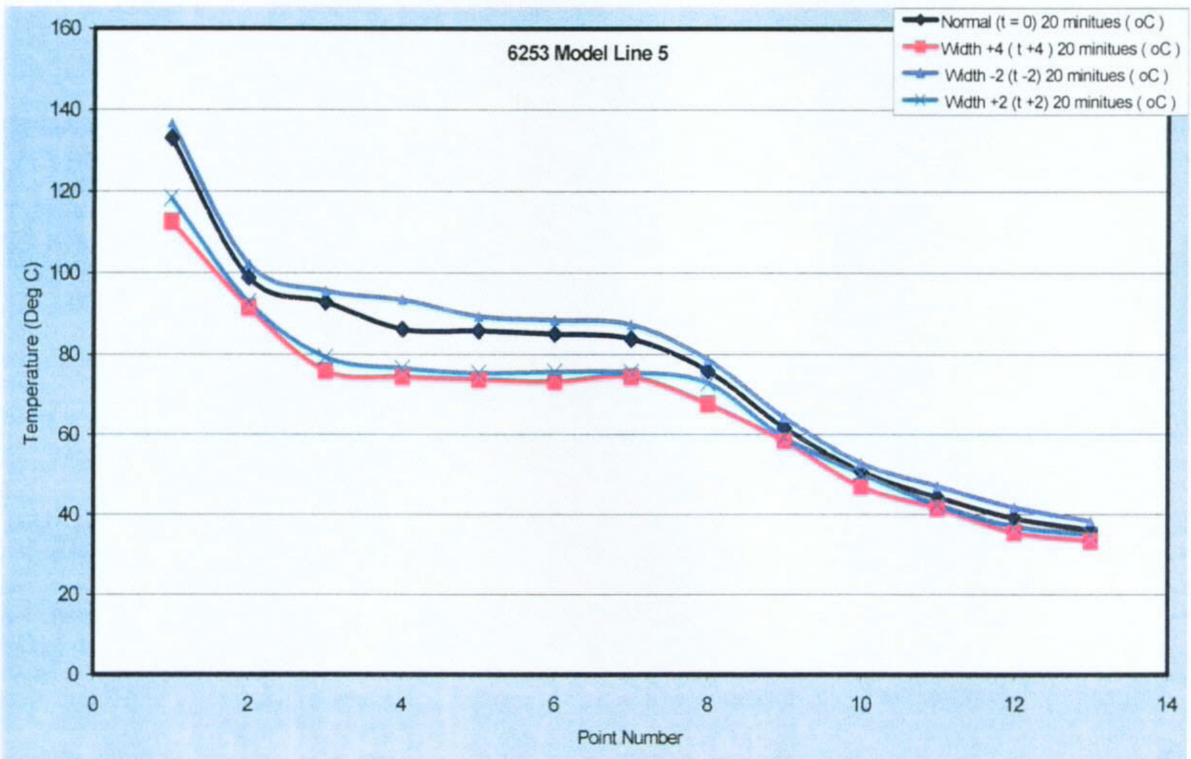


Fig. 32 Purified Data Set for the Toaster in Line 1 Location

4.8.1 *Network Input Determination and Setup of Training Schema*

In this study, the coordinates of a geometry (X, Y, Z) were selected for the analysis and a reinforced training parameter, the absolute distance D (distance between the chassis and the toaster case outer surface) was also included. Therefore, there existed four training inputs and one target output i.e. the temperature on the toaster surface. In order to avoiding over-training, the input training data was divided into three sections, known as the training, verification and testing data (Fig. 33). Two training schemas were set known as (i) the whole set approach, and (ii) the divided approach. The detail training schema for the first study was shown in Fig.34.

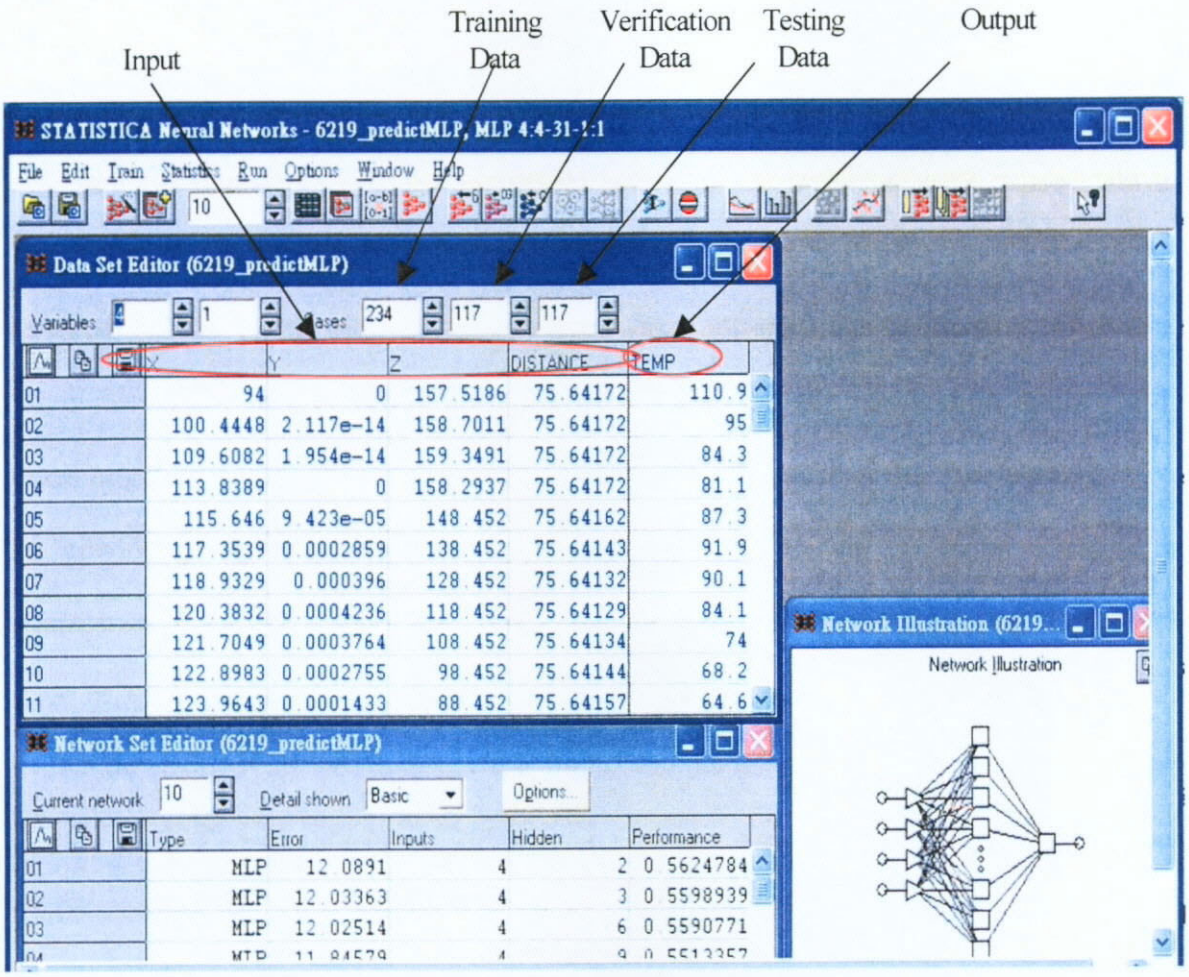


Fig. 33 Screenshot of the Neural Network Training

	Divided approach Split each line into 3 zones and construct network for each segment	Whole set approach Use the data of each line to construct the network
Multiple Layer Perceptron (MLP)	Schema: 1A	Schema : 1B
Radial Basis Feedforward (RBF)	Schema: 2A	Schema : 2B

NN training condition -2mm +4mm +2mm Normal

NN prediction condition +3mm

Permissible Deviation of the predicted temperature
= Predicted Temperature – Actual Temperature < - 10°C

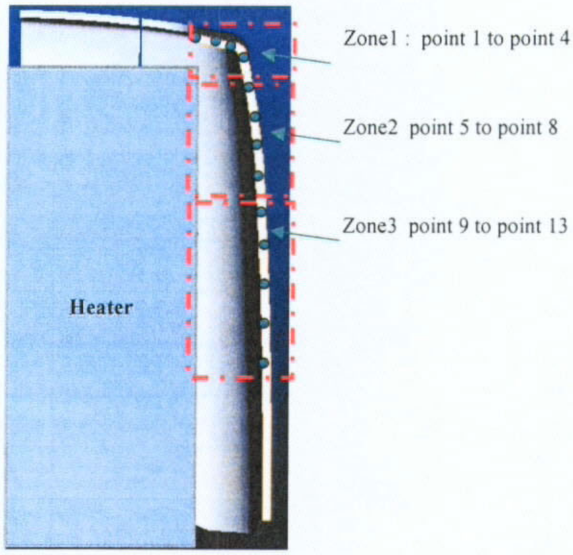


Fig. 34 The Training Schemas for the First Investigation

4.8.2 *The Best ANN Algorithm Selection*

The data sets were training in four different ways and their root-mean-square (RMS) errors were used for monitoring. At predetermined intervals, the trainings were paused and the current weights were measured. Before a training resumed, the pre-mature network was presented with the verification data and its error was monitored. The verification errors of the studies decreased steadily before they stabilized. However, the verification errors for the studies might pass through a minimum and then rebound because of the over-training effect. The previously stored set of weight would be closed to the optimum. Finally, the performance of the ANN algorithm was evaluated. The training results of the ANNs were shown in Tables 4 to Table 7. By comparisons of the testing errors, training errors and the verification errors of all the studies, it was found that the RBF algorithm had the lowest error in "schema 100" while "schema 29" was the lowest for the MLP algorithm. The best performance for this investigation was schema 29 whilst the network weight distributions were shown in the Fig. 35 and Fig 36.

Table 4 Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 1)

Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
3	MLP	7.99	4.00	3.00	4.77	7.99	8.52
4	MLP	7.39	4.00	4.00	1.84	7.39	8.45
5	MLP	7.27	4.00	5.00	1.95	7.27	8.32
7	MLP	7.24	4.00	7.00	1.27	7.24	8.21
11	MLP	7.18	4.00	11.00	1.59	7.18	7.99
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
36	RBF	8.23	4.00	36.00	4.35	8.23	7.95
49	RBF	7.57	4.00	49.00	2.70	7.57	7.33
52	RBF	7.54	4.00	52.00	2.29	7.54	7.24
53	RBF	7.54	4.00	53.00	2.20	7.54	7.22
54	RBF	7.52	4.00	54.00	2.13	7.52	7.17

Table 5 Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 2)

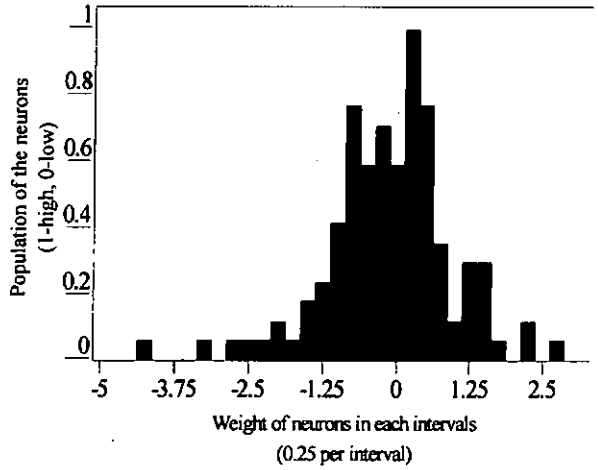
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
4	MLP	6.14	4.00	4.00	1.91	5.90	6.14
8	MLP	5.81	4.00	8.00	6.36	5.48	11.43
9	MLP	5.72	4.00	9.00	4.97	5.47	10.06
16	MLP	5.64	4.00	16.00	3.01	5.44	7.03
25	MLP	5.56	4.00	25.00	2.25	5.35	6.83
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
12	RBF	6.68	4.00	12.00	4.52	7.93	6.54
19	RBF	5.80	4.00	19.00	4.22	7.69	6.44
29	RBF	5.77	4.00	29.00	3.16	7.56	5.65
45	RBF	5.77	4.00	45.00	1.21	5.53	6.06
68	RBF	5.71	4.00	68.00	1.07	5.34	6.12

Table 6 Summary of the Network Setting and Training Results for RBF and MLP with Divided Approach (Zone 3)

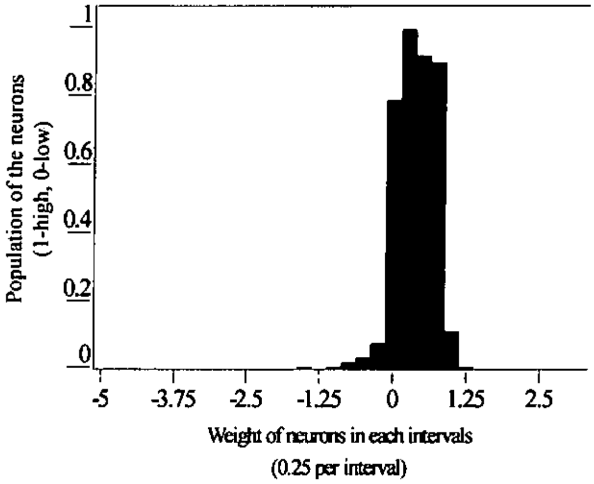
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
6	MLP	3.04	4.00	6.00	4.26	3.04	8.22
8	MLP	2.94	4.00	8.00	4.05	2.94	7.71
10	MLP	2.69	4.00	10.00	4.77	2.69	8.74
13	MLP	2.68	4.00	13.00	4.63	2.68	8.33
20	MLP	2.63	4.00	20.00	3.73	2.63	7.65
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
12	RBF	6.61	4.00	12.00	5.17	6.61	6.82
13	RBF	5.81	4.00	13.00	4.32	5.81	5.99
14	RBF	5.72	4.00	14.00	4.28	5.72	6.36
15	RBF	5.46	4.00	15.00	4.09	5.46	6.16
16	RBF	4.94	4.00	16.00	3.36	4.94	5.62

Table 7 Summary of the Network Setting and Training Results for RBF and MLP with Whole Set Approach

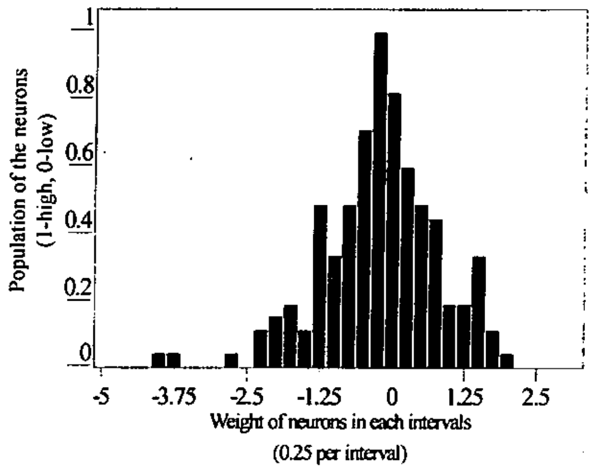
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
29	RBF	16.55	4	29	15.90	16.55	16.45
45	RBF	14.97	4	45	13.77	14.97	14.51
68	RBF	9.68	4	68	7.11	9.68	8.70
79	RBF	7.78	4	79	5.94	7.78	10.22
100	RBF	6.67	4	100	4.95	6.67	9.23
Training scheme	Type	Error	Inputs	No. of neurons	TError	VError	TeError
2	MLP	5.29	4	2	3.64	5.29	6.35
5	MLP	5.47	4	5	4.85	5.47	7.69
6	MLP	5.20	4	6	3.62	5.20	6.49
7	MLP	5.23	4	7	3.93	5.23	7.00
29	MLP	4.33	4	29	3.13	4.33	7.17



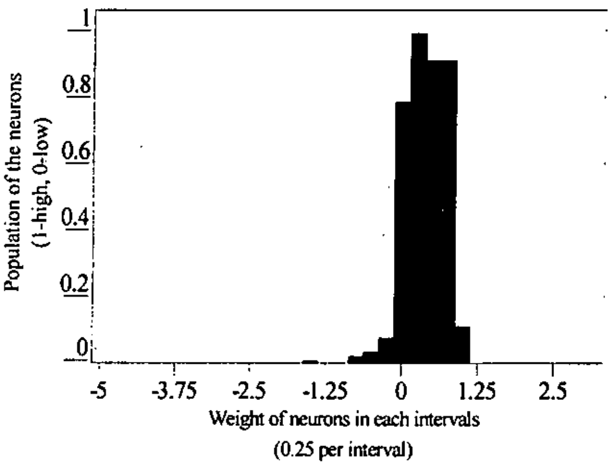
(a) MLP in Divided Approach (Zone 1)



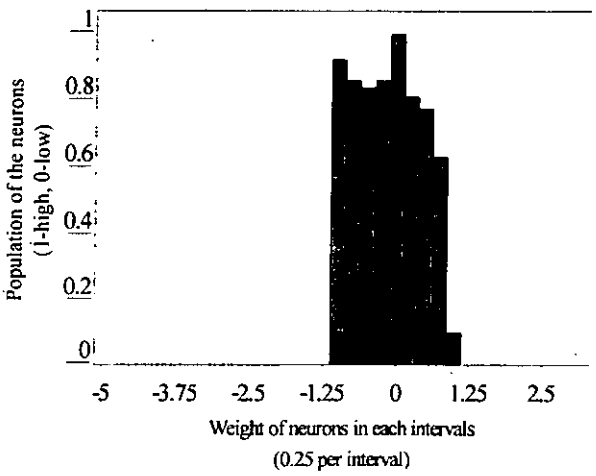
(b) MLP in Divided Approach (Zone 1)



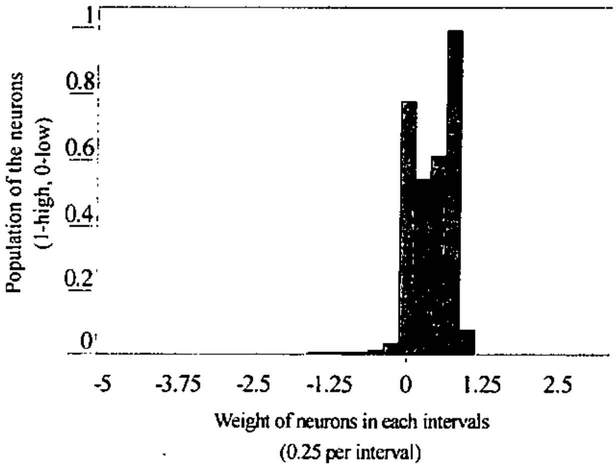
(c) MLP in Divided Approach (Zone 2)



(d) RBF in Divided Approach (Zone 2)

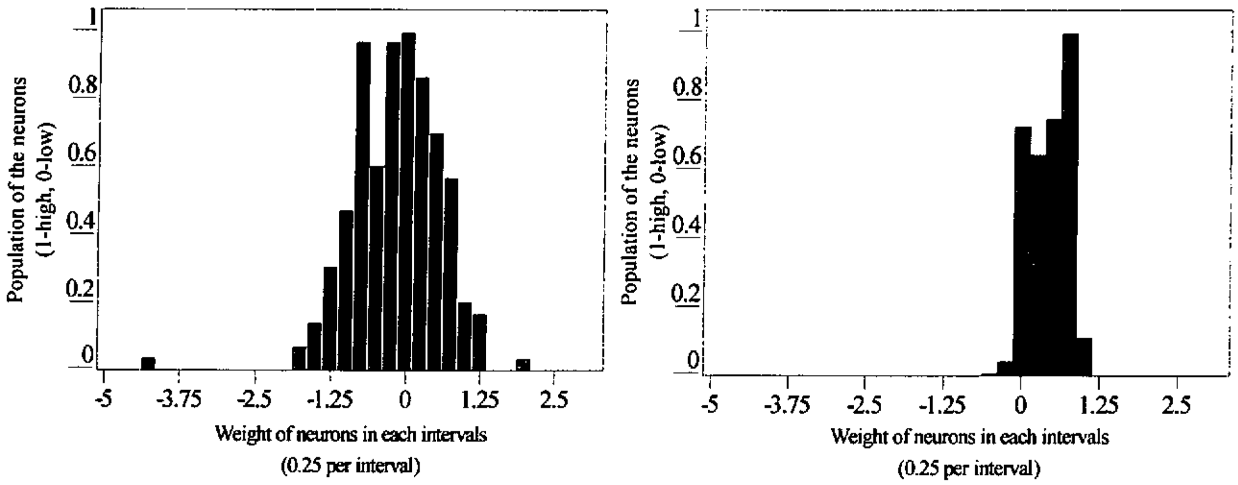


(e) MLP in Divided Approach (Zone 3)



(f) RBF in Divided Approach (Zone 3)

Fig. 35 Final Weight Distribution for the MLP and RBF Algorithms in Divided Approach



(a) MLP in Whole Set Approach

(b) RBF in Whole Set Approach

Fig. 36 Final Weight Distribution for the MLP and RBF Algorithms in Whole Set Approach

4.9 Investigation 2 - Prediction of an Entirely New Toaster Case Design from Existing Styles

The second investigation was aimed to test the capability of the KIC for the prediction of a completely new toaster/design geometry. To start with the investigation, data sets of three different toaster cases were used to build up the knowledge database. Similarly to the previous study, the data sets were trained properly to form a new knowledge database for the prediction of toaster case temperature under the working condition for the fifth and sixth models.

4.9.1 Training Schema for the Fifth Toaster Case Temperature Prediction

Similarly, geometry data with x,y,z coordinates, a reinforced design parameter distance D and case temperature were input to the training process. In the second study, two training schemas were also assigned: the first schema is multi-style with single normal size (468 data) and the second schema is multi-style with multi layers (1,872 data) input. The detail schema for the study was shown in Fig. 37.

	Training data set =1872 (Multi-Style/ Multi-layer)	Training data set = 468(Multi-Style/ Single Layer
Multiple Layer Perceptron(MLP)	Schema: 1A	Schema: 2A
Radial Basis Feedforward(RBF)	Schema : 1B	Schema : 2B

Permissible Deviation of the predicted temperature

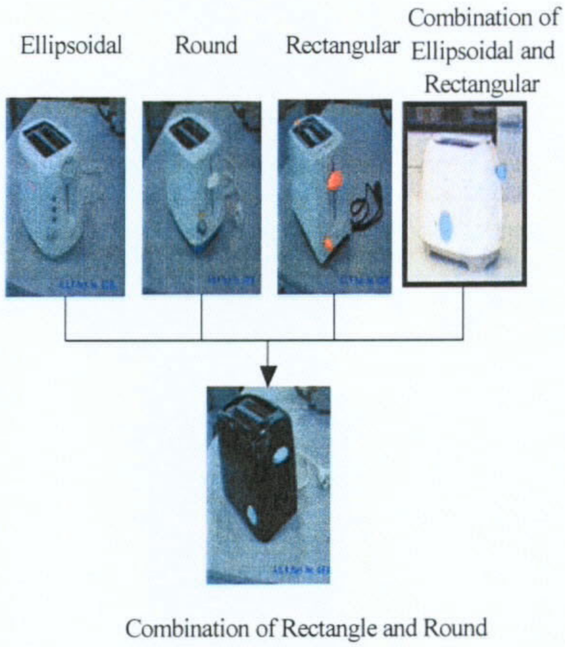


Fig. 37 Schema for the Setup of Investigation 2

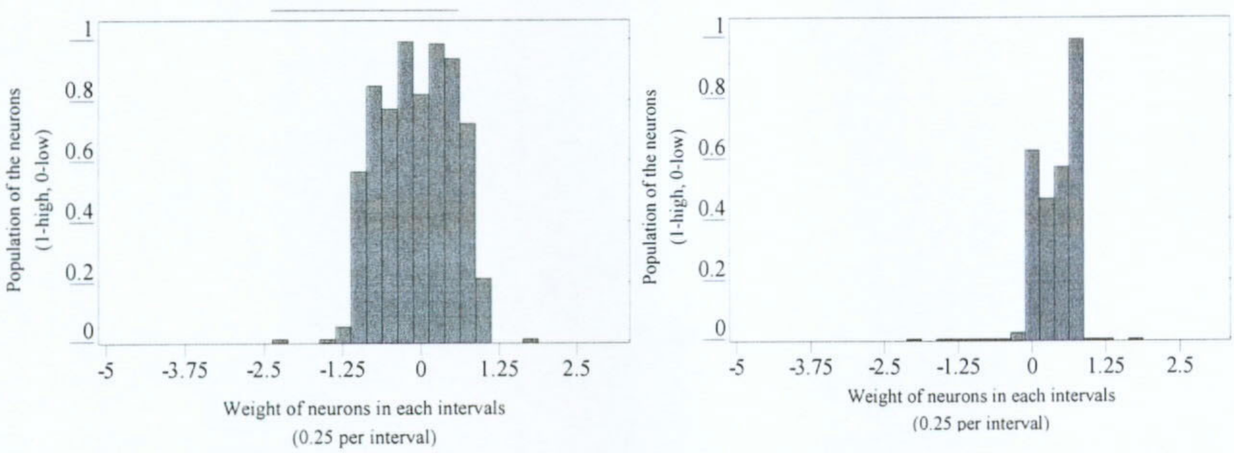
4.9.1.1 Investigation I with 468 Data Sets – Multi-Style/Single Layer

Having gone through the same training process mentioned in the first study, the training results for each of the network topology were recorded and shown in Table 8.

By comparison with the test errors, training errors and the verification errors of all training schemas, for the RBF algorithm, the lowest error was found in schema 112 while schema 28 gave the lowest error for the MLP algorithm. The best performance for this investigation was given by schema 28 and the network weight distributions were shown in the Fig. 38.

Table 8 Summary of the Network Setting for RBF and MLP with 468 Data Sets

Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
116	RBF	11.49	4	116	6.99	11.49	9.10
117	RBF	11.47	4	117	6.92	11.47	8.98
118	RBF	10.91	4	118	6.77	10.91	9.32
120	RBF	10.74	4	120	6.73	10.74	8.71
121	RBF	10.61	4	121	6.67	10.61	8.84
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
6	MLP	9.27	4	6	13.36	9.27	13.41
18	MLP	8.81	4	18	10.11	8.81	12.81
19	MLP	8.78	4	19	9.97	8.78	12.92
26	MLP	8.77	4	26	12.63	8.77	13.13
28	MLP	8.54	4	28	13.45	8.54	13.84



(a) MLP Algorithm with 468 Data Set b) RBF Algorithm with 468 Data Set

Fig. 38 Final Weight Distribution for the MLP and RBF Algorithm with 468 Data Set

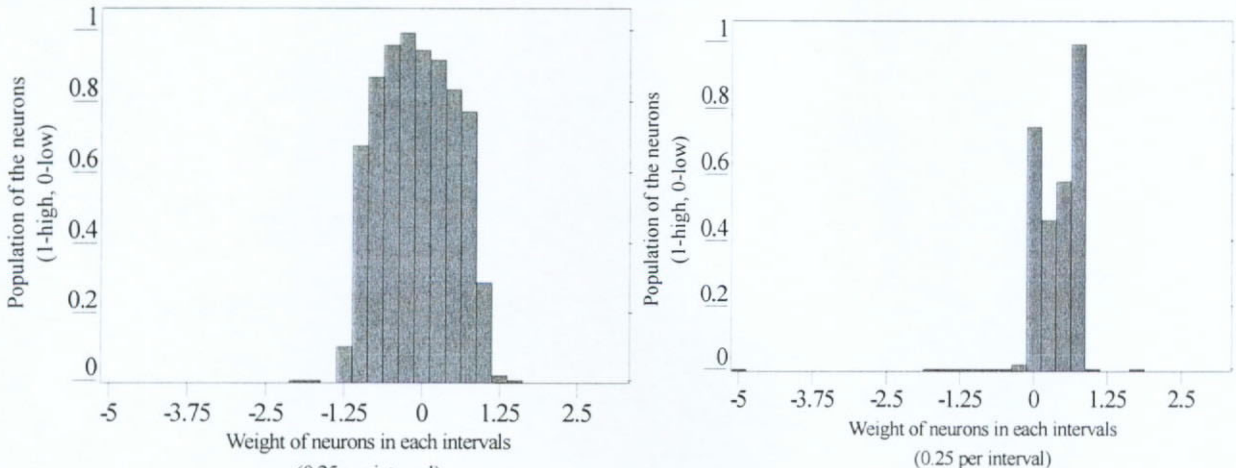
4.9.1.2 Investigation 2 with 1872 Data Sets – Multi-Style/Multi-Layers

Similar to the previous investigation, this investigation went through the same training process and the training results for each of the network topology were recorded and shown in Table 9.

Based on the comparison with the test errors, training errors and the verification errors of all training schemas, for the RBF algorithm gave the lowest error in schema 58 while errors of schema 14 was the lowest for the MLP NN algorithm. The best performance for this investigation was schema 14. Therefore, the choice of the best NN candidate was MLP in this round. The network weight distributions were shown in the Fig. 39.

Table 9 Summary of the Network Setting for RBF and MLP with 1872 Data Sets

Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
49	RBF	10.10	4	49	5.90	10.10	16.45
54	RBF	9.80	4	54	5.42	9.80	14.51
56	RBF	9.29	4	56	4.90	9.29	8.70
57	RBF	9.28	4	57	4.86	9.28	10.22
58	RBF	9.27	4	58	4.85	9.27	9.23
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
1	MLP	10.56	4	1	10.13	10.56	10.10
2	MLP	10.54	4	2	10.12	10.54	9.86
4	MLP	10.44	4	4	10.10	10.40	9.88
6	MLP	10.32	4	6	9.89	10.32	9.71
9	MLP	10.26	4	9	9.77	10.26	9.65



(a) MLP Algorithm with 1872 Data Set b) RBF Algorithm with 1872 Data Set

Fig. 39 Final Weight Distribution for the MLP and RBF Algorithm with 1872 Data Set

4.9.2 Setup of Training Schema of the Sixth Toaster Case Temperature Prediction (Multi-Style/Multi-Layers)

This study was used to further confirm the establishment of a knowledge spiral in the study that can refine and increase the ability/performance of the knowledge system (Fig. 40). Based on the previous knowledge database establishment, another new toaster case was brought for prediction for the performance confirmation of the KIC system. The number of training data sets for the study was increased from 1,872 to 1,989 (1872 +117 with new predicted model).

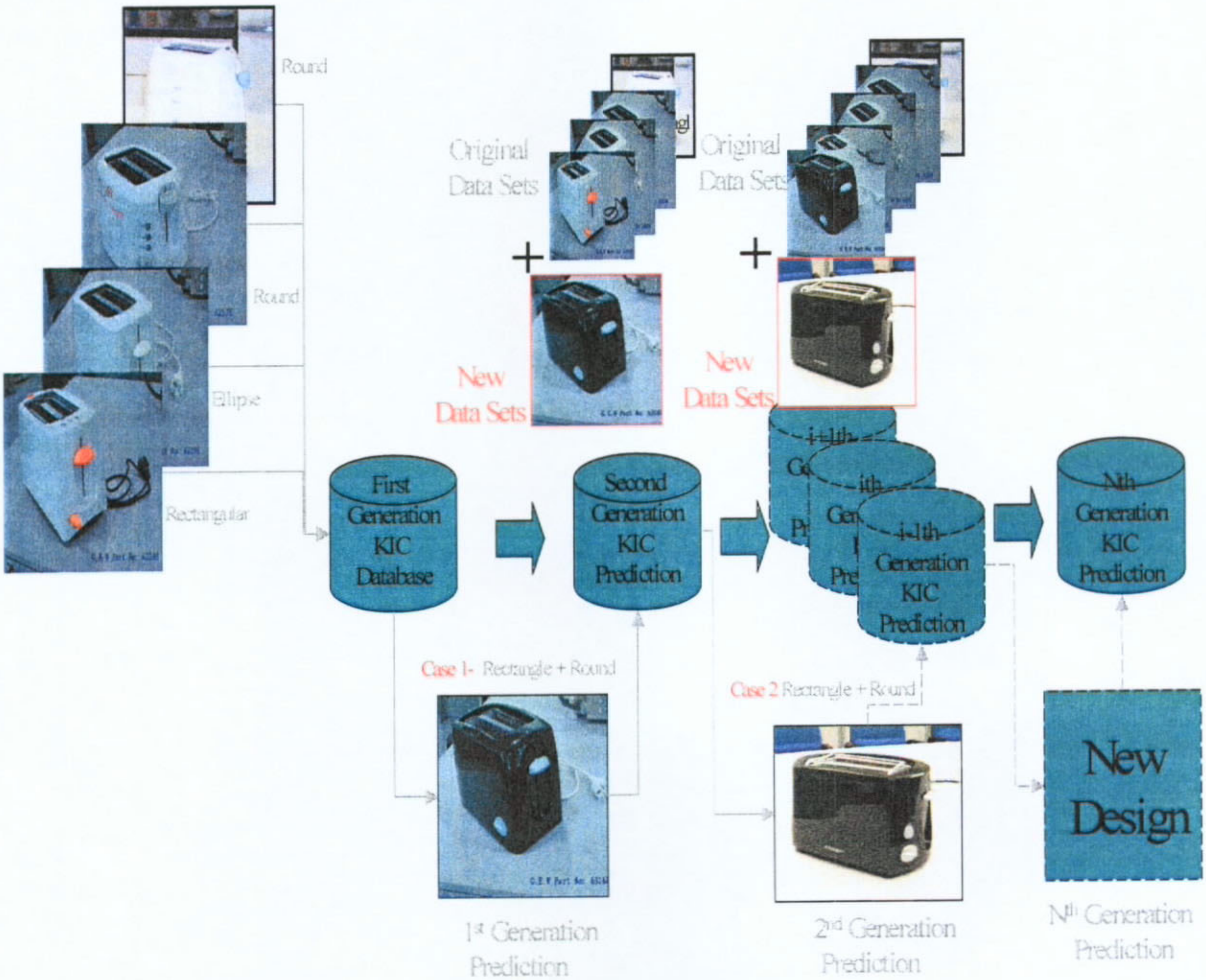


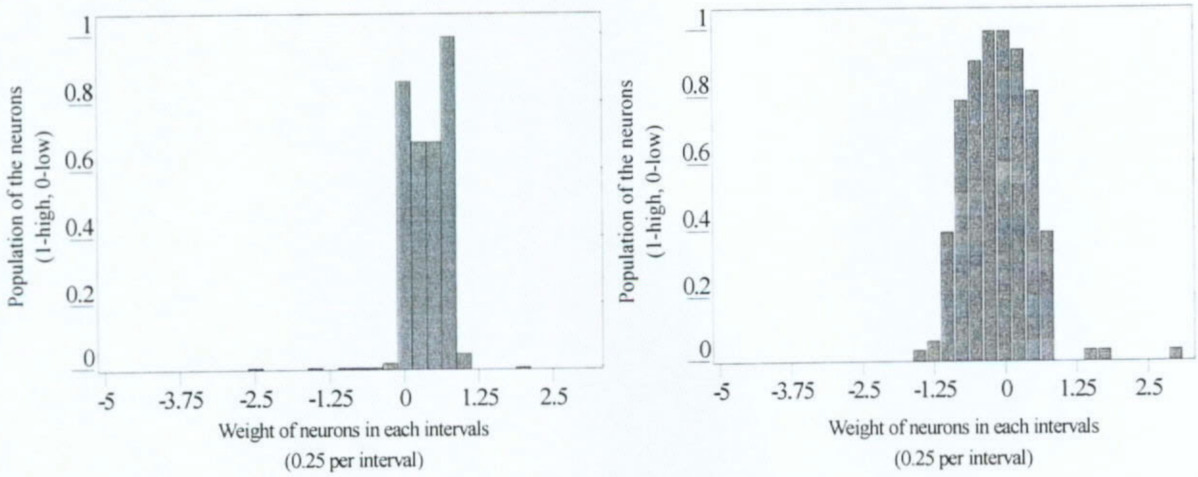
Fig. 40 Generation of the Knowledge Spiral

4.9.2.1 Selection of the Best NN Algorithm

Table 10 Summary of the Network Setting for RBF and MLP

Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
118	RBF	8.95	4	118	7.88	8.95	9.30
120	RBF	8.95	4	120	7.88	8.95	9.30
121	RBF	8.94	4	121	7.87	8.94	9.30
123	RBF	8.93	4	123	7.87	8.93	9.29
124	RBF	8.93	4	124	7.87	8.93	9.29
Training Scheme	Type	Error	Inputs	Hidden	Training Error	Verification Error	Testing Error
1	MLP	8.68	4	1	7.74	8.68	7.69
3	MLP	8.64	4	3	5.57	8.64	6.35
6	MLP	8.52	4	6	3.75	8.52	7.00
8	MLP	8.47	4	8	6.39	8.47	6.49
14	MLP	8.39	4	14	5.85	8.39	7.17

By comparison with the test errors, training errors and the verification errors of all training schemas, for the RBF algorithm gave the lowest errors with schema 124 while schema 9 was the lowest for the MLP algorithm. The best performance for appeared in schema 9 and the best ANN candidate was MLP. The network weight distributions were shown in the Fig. 41.



(a) MLP Algorithm with 1989 Data Set (b) RBF Algorithm with 1989 Data Set

Fig. 41 Final Weight Distribution for the MLP and RBF Algorithm

4.10 Deployment of the KIC

After the establishment of the validation of the KIC knowledge database, the next step was to deploy the system for regular usage. The deployment process consisted of the building up of an automatic slicing program to determine the coordinates of toaster case design for temperature inquiry. Furthermore, a web-centric graphical user interface for geometry input and the displacement of temperature prediction were built.

A user can then be based on the temperature prediction to make a decision whether a design can be acceptable or not and take any required remedial actions for a design modification. From now on, the engineers in the company can make use the KIC system for the prediction of temperature, and together with the use of CAE software to determine the thermal displacement of a similar or entirely new toaster design. The results of temperature gradient and thermal strain displacement of the case study were shown in Fig. 42 to Fig. 50.

Fig. 42 Main Screen of the Knowledge Portal

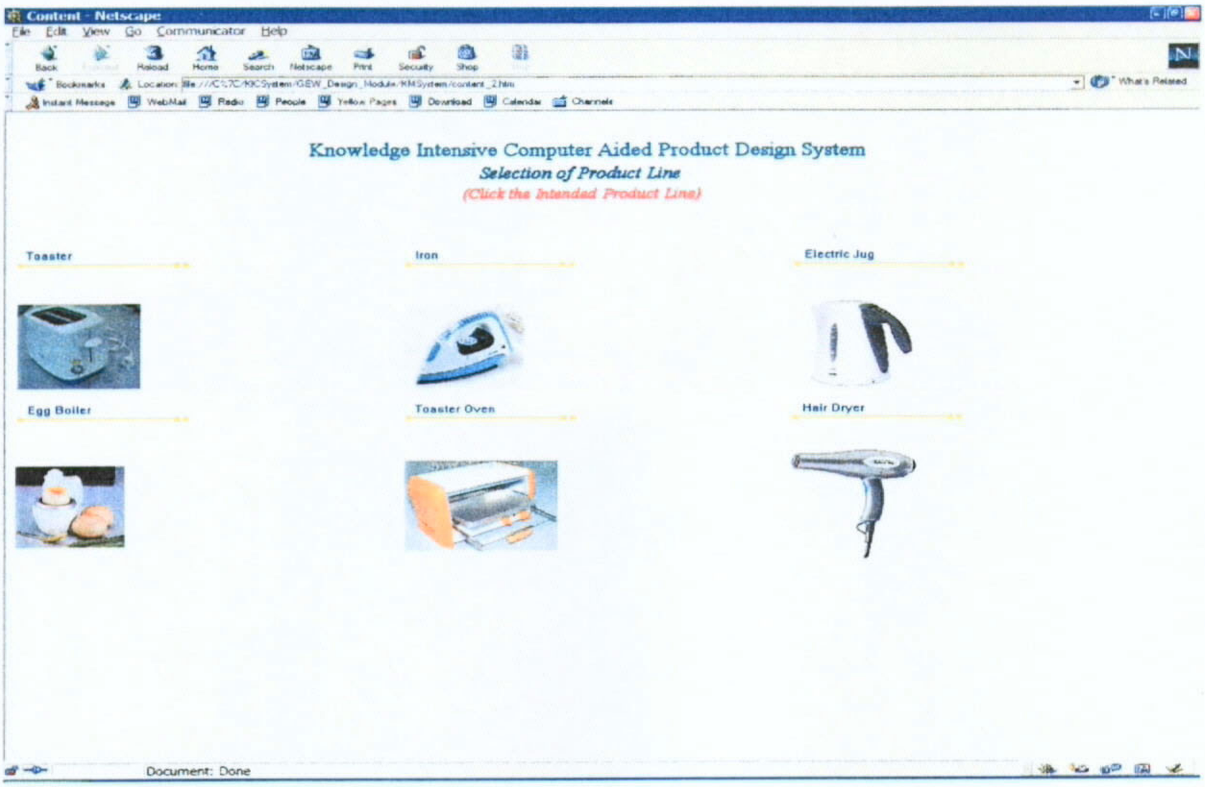


Fig. 43 Screen Shot of the Product Line Selection

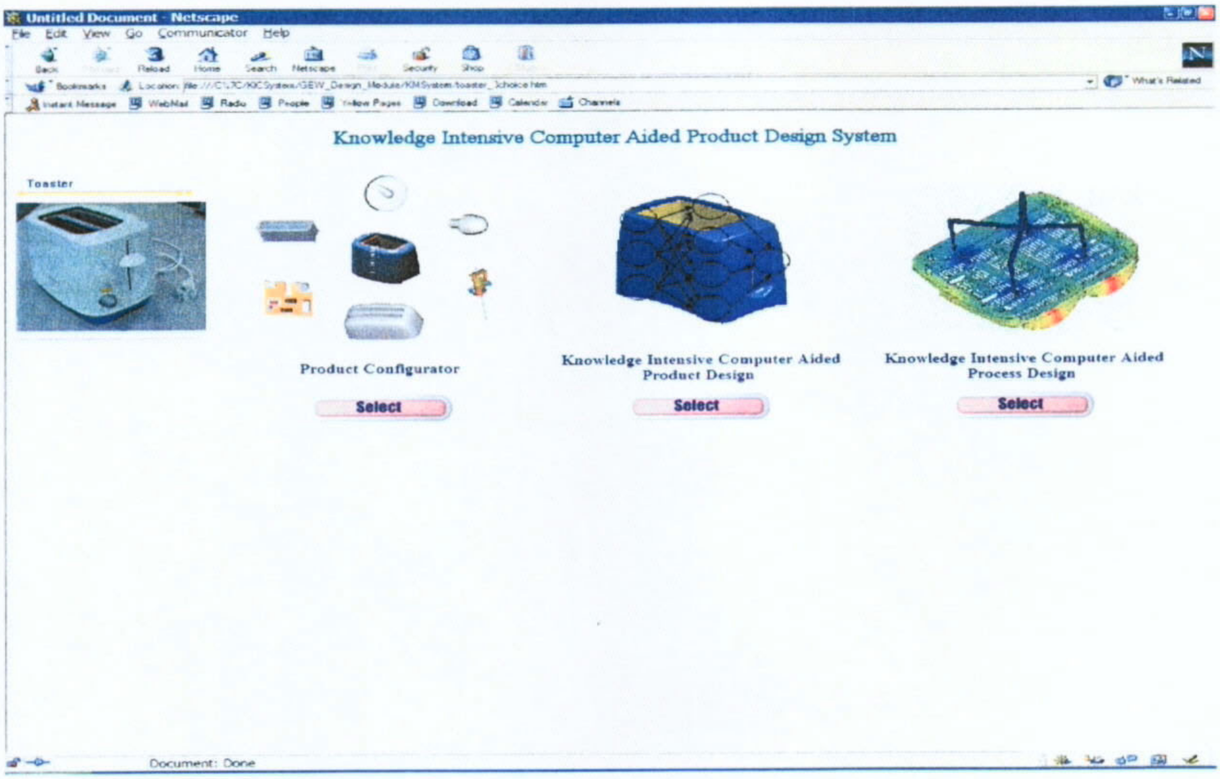


Fig. 44 Screen Shot for KIC System Module Selection

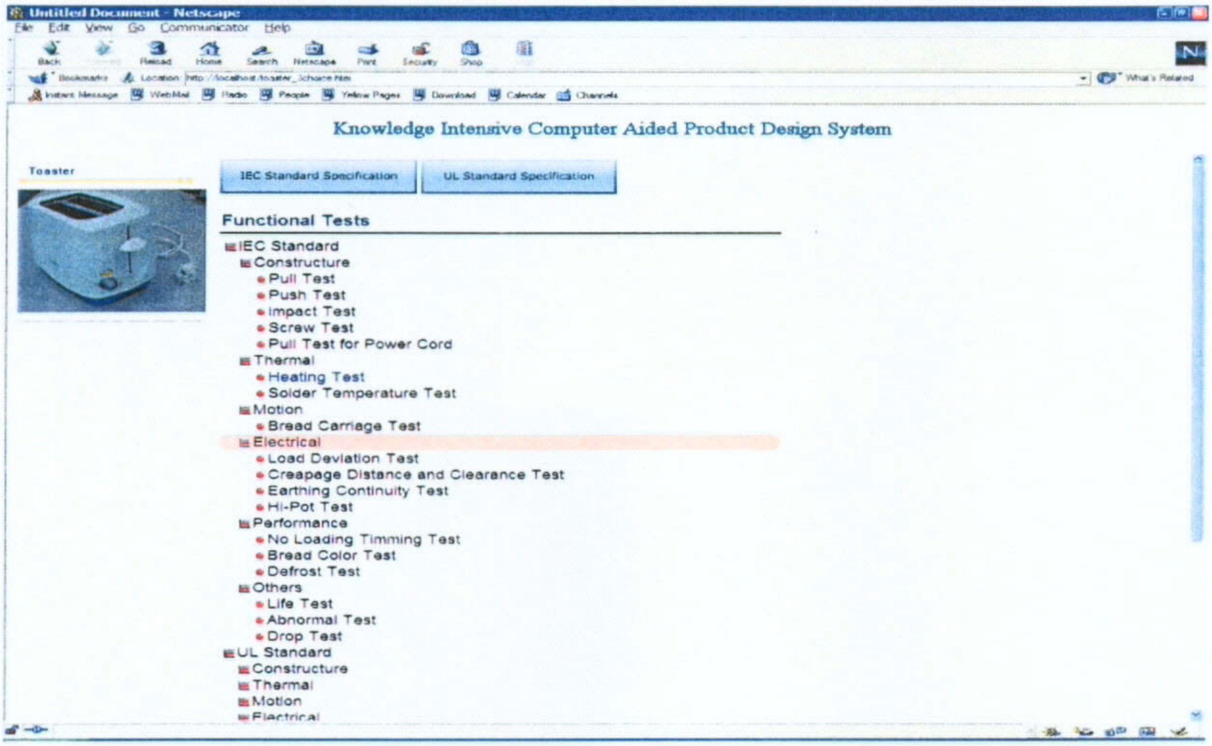


Fig. 45 Screen Shot of Functional Test Selection – the Heating Test Module

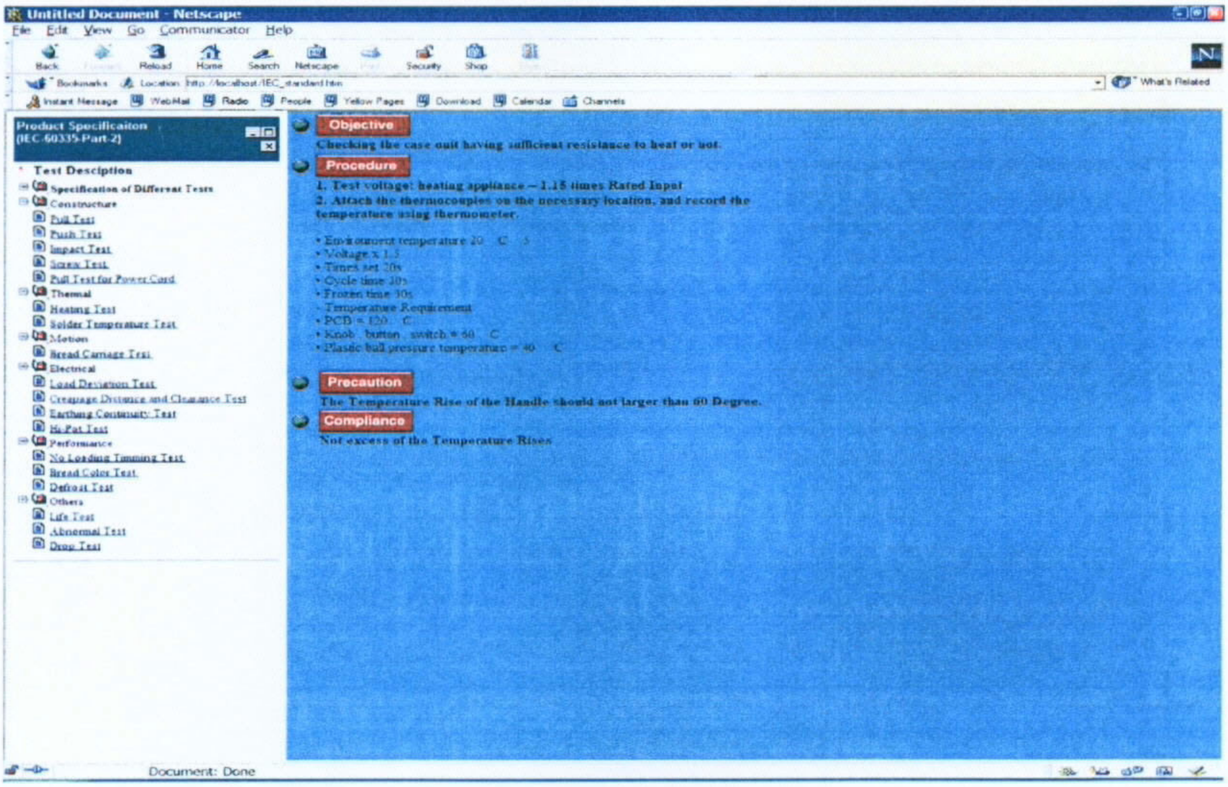


Fig. 46 Screen shot of the Help Document in Each Product Test

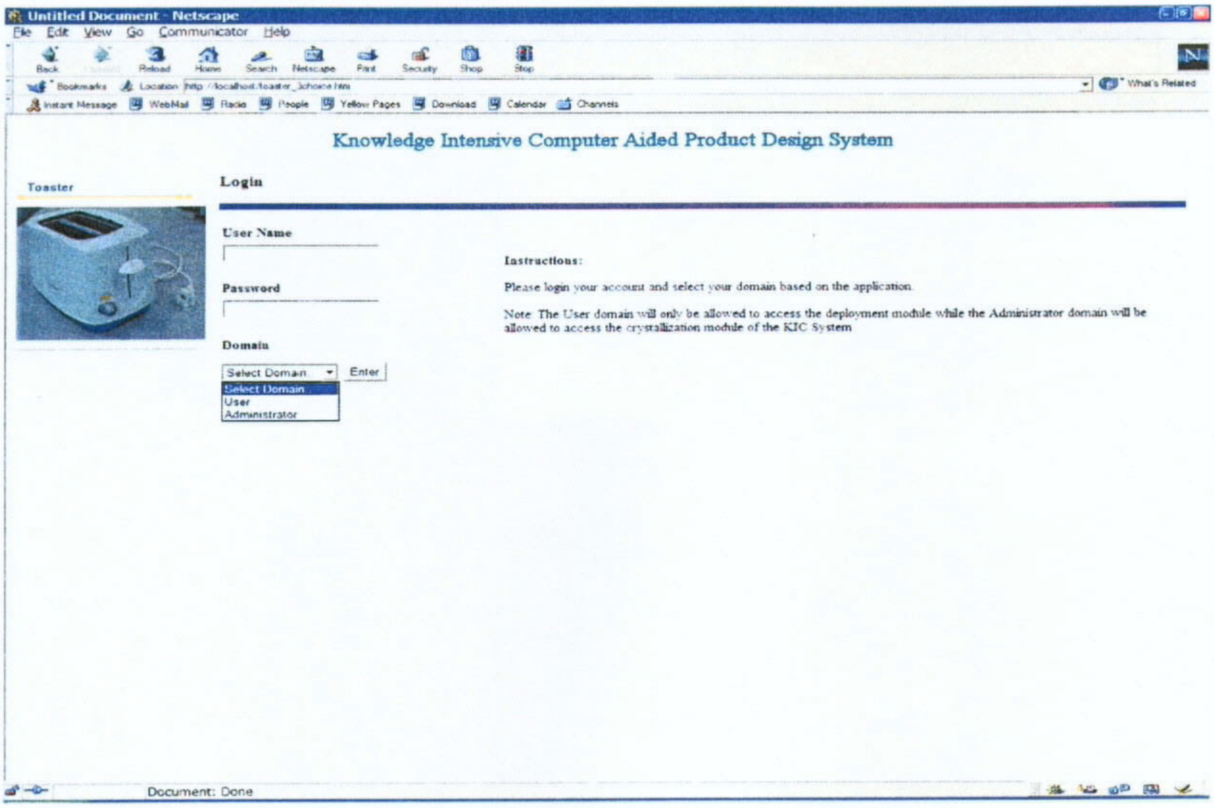


Fig. 47 Screen Shot for Login - Accessing the KIC Module

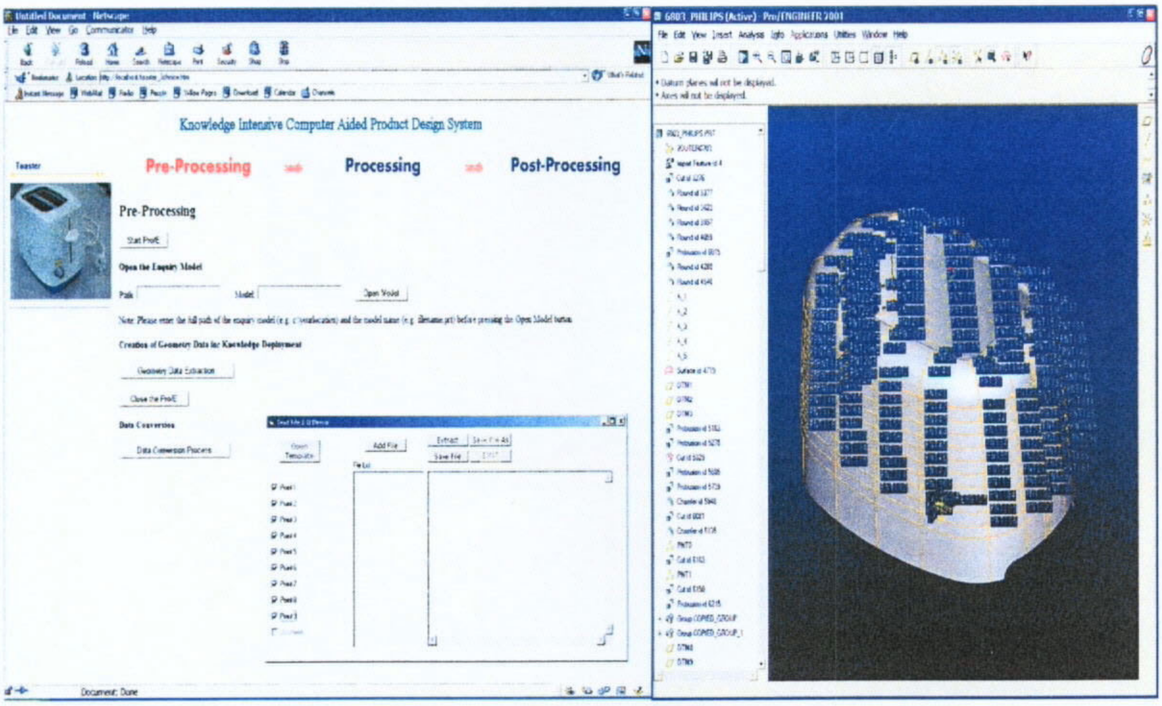


Fig. 48 Screen Shot of the Slicing Program

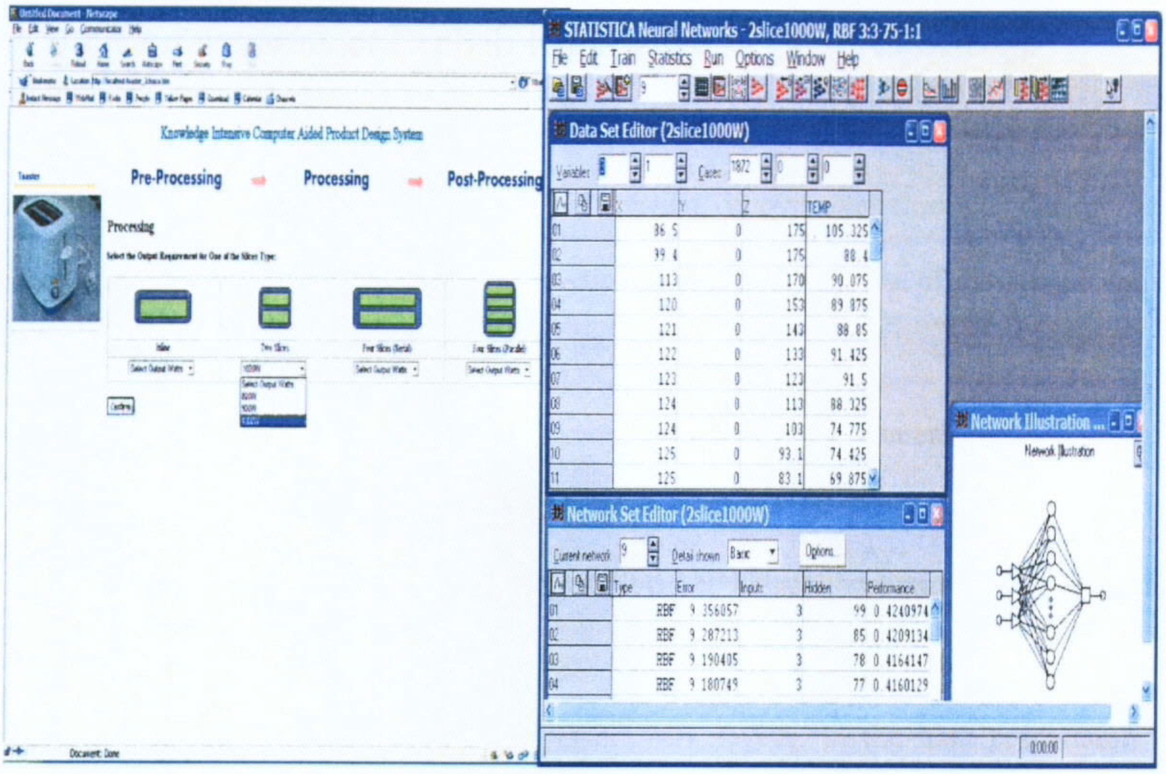


Fig. 49 Screen Shot of the Retrieval of the Codified Knowledge and Execute a Prediction

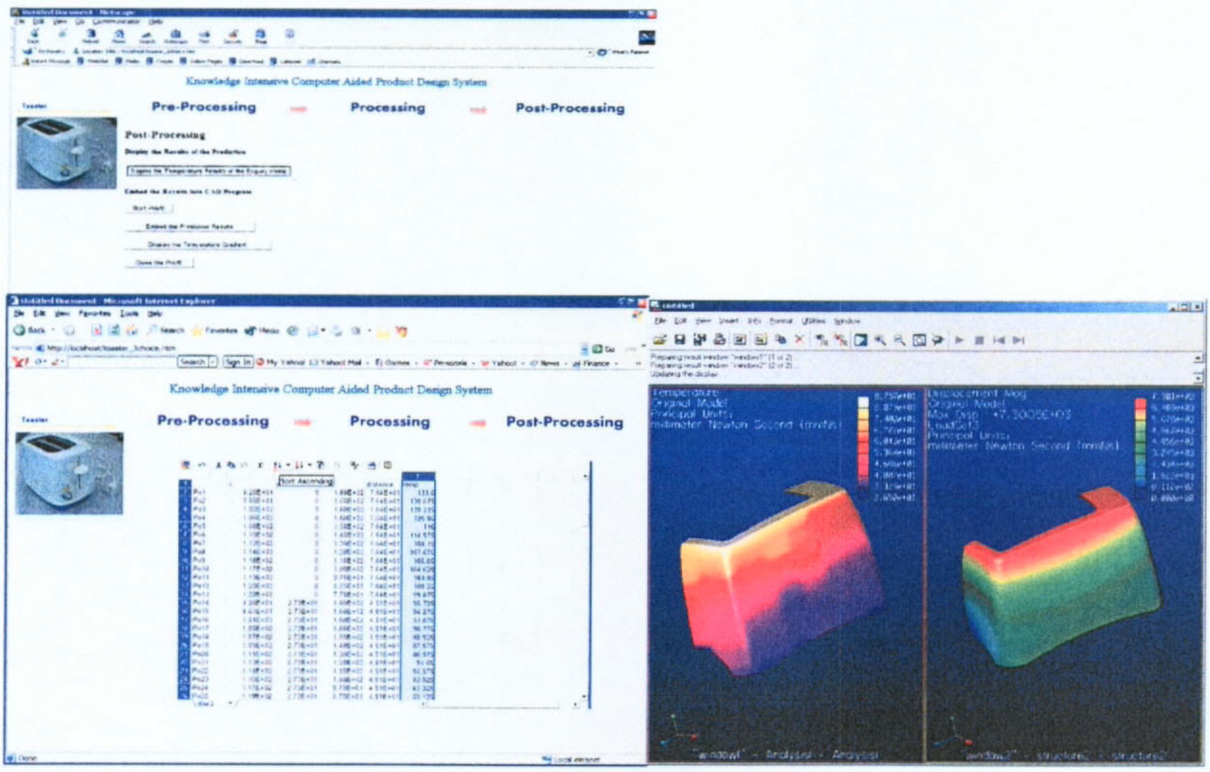


Fig. 50 Screen Shot of the Post-processing - Display of Predicted Result

Chapter 5 Results and Discussions

5.1 Transformation of Explicit Knowledge to Tacit Knowledge

From the results of the two investigations, it was found that tactic knowledge of isolated toaster cases could be transformed to explicit knowledge through the proposed methodology and could be reused to predict surface temperature of similar or entirely new case designs.

In the formulation of the tacit knowledge, the accuracy of raw data and the ANN training were the utmost important issues because the prediction capability of a KIC system will highly rely on the work done in these stages give ANN algorithms are inductive in nature, their constructed knowledge is high dependent on the data presented. Therefore, the accuracy of the prediction of a KIC system will be cast in the data preparation and training stages whilst an effective way for the screening of errors and noise and recognition is the key of success.

5.2 Performance of the KIC System for the Heating Test

5.2.1 Prediction Accuracy of the First Investigation for a Dedicated Style and Variable Sizes

In the first investigation, two issues were observed. Firstly, the performances of the two selected ANN algorithms (MLP and RBF) were different but both within the temperature tolerance variation that could be accepted. The deviations of the MLP and RBF predictions to the actual toaster case temperature distributions from line 1 to line 9 are shown in Fig. 51 to 54. In the figures, no upper limit was set become over prediction could be tolerated, because it is less risky than over prediction. The allowed/acceptable tolerance zone of temperature estimation is shown in pink.

The predictions of MLP algorithms with the divided approach failed at the toaster case back (zone 1) and the front corners (zone 9). It was found that, the MLP algorithms with the "whole set" approach and RBF with both approaches could both acceptable that within the allowable zones. However, the predictions were biased to the positive (higher) limit and only a small amount of predictions were felt into the lower limit zone. The results of the prediction, the sizes of data sets, the required NN training times and sizes of the KIC database were summarized and tabulated with the divided and whole set approach in Table 11. From the table, it was confirmed that: (i), the performance of MLP was better than RBF in the whole set approach with a maximum temperature deviation of 12.26°C and a standard deviation of 2.74 whilst RBF gave a maximum temperature deviation 17.86°C and a standard deviation 4.45 respectively. The average accuracy of prediction made by MLP was 38.43% better than RBF and (ii) the "whole set approach" should be used always in a knowledge crystallization process since the common believe "the fewer the better in data fitting" did not apply in the study.

Table 11. Summary of All the Temperature Results from Line 1 to Line 9 (Investigation 1)

	Max Temperature Difference (Divided Approach)				Max Temperature Difference (Whole Set Approach)			
	MLP (Maximum (Temperature Difference)	No of point out of Limit (T°C> -10)	RBF (Maximum (Temperature Difference)	No of point out of Limit (T°C> -10)	MLP (Maximum (Temperature Difference)	No of point out of Limit (T°C> -10)	RBF (Maximum Temperature Difference)	No of point out of Limit (T°C> -10)
Line 1	-12.43	1 pt over predicted but within preset limit(reject)	14.55	0 out of 13	6.95	0 out of 13	17.8 6	0 out of 13
Line 2	-14.79	1 pt over predicted but within preset limit (reject)	13.4 1	0 out of 13	12.26	0 out of 13	13.67	0 out of 13
Line 3	9.32	0 out of 13	7.90	0 out of 13	8.15	0 out of 13	7.51	0 out of 13
Line 4	4.32	0 out of 13	3.66	0 out of 13	1.52	0 out of 13	5.7 1	0 out of 13
Line 5	-4.06	0 out of 13	5.3 4	0 out of 13	5.88	0 out of 13	5.9 4	0 out of 13
Line 6	4.87	0 out of 13	5.40	0 out of 13	5.14	0 out of 13	6.78	0 out of 13
Line 7	5.69	0 out of 13	4.41	0 out of 13	5.62	0 out of 13	3.49	0 out of 13
Line 8	10.90	0 out of 13	7.40	0 out of 13	8.8 6	0 out of 13	6.33	0 out of 13
Line 9	7.19	0 out of 13	13.00	0 out of 13	5.24	0 out of 13	13.9 3	0 out of 13
Total	Failed	Total 2 pts exceed preset limit	100% Pass	Total 0 pt exceed within preset limits	100% Pass	Total 0 pt exceed within preset limits	100% Pass	Total 0 pt exceed within preset limits
No of Training Data	468		468		468		468	
Training Time(mins)	466		430		442		402	
Size of Database (Mbytes)	1		1		1		1	

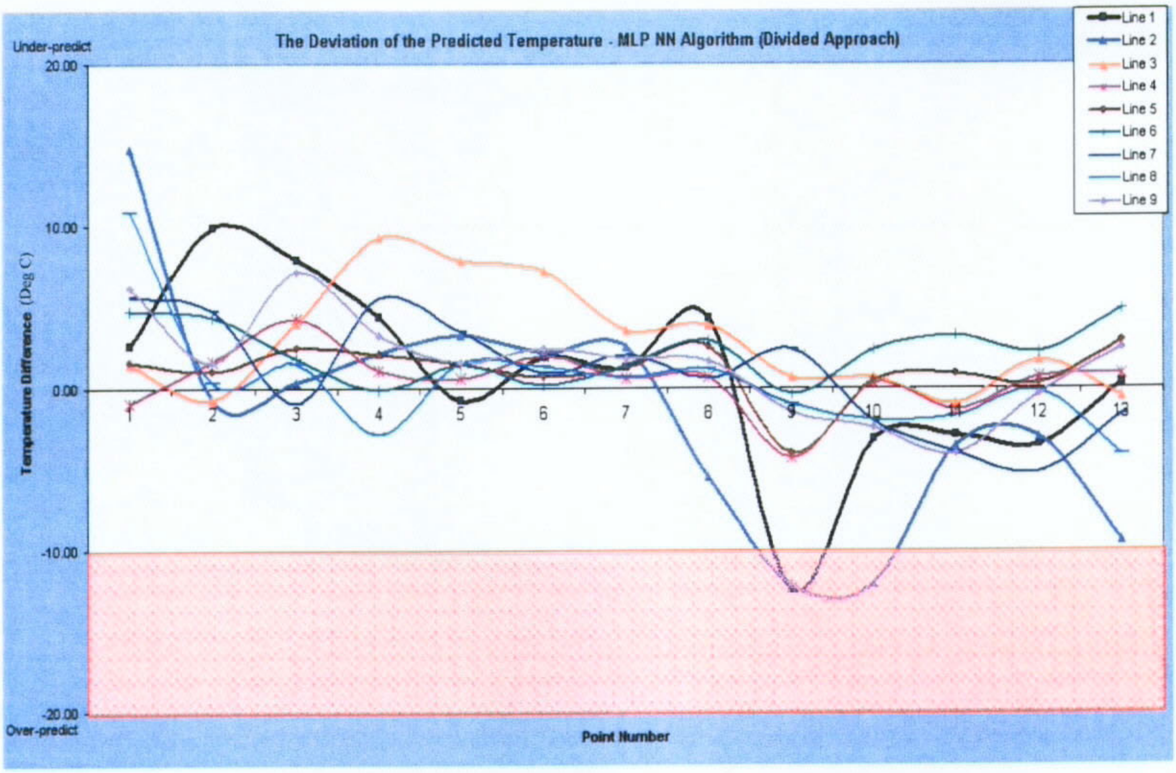


Fig. 51 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(MLP with Divided Approach)

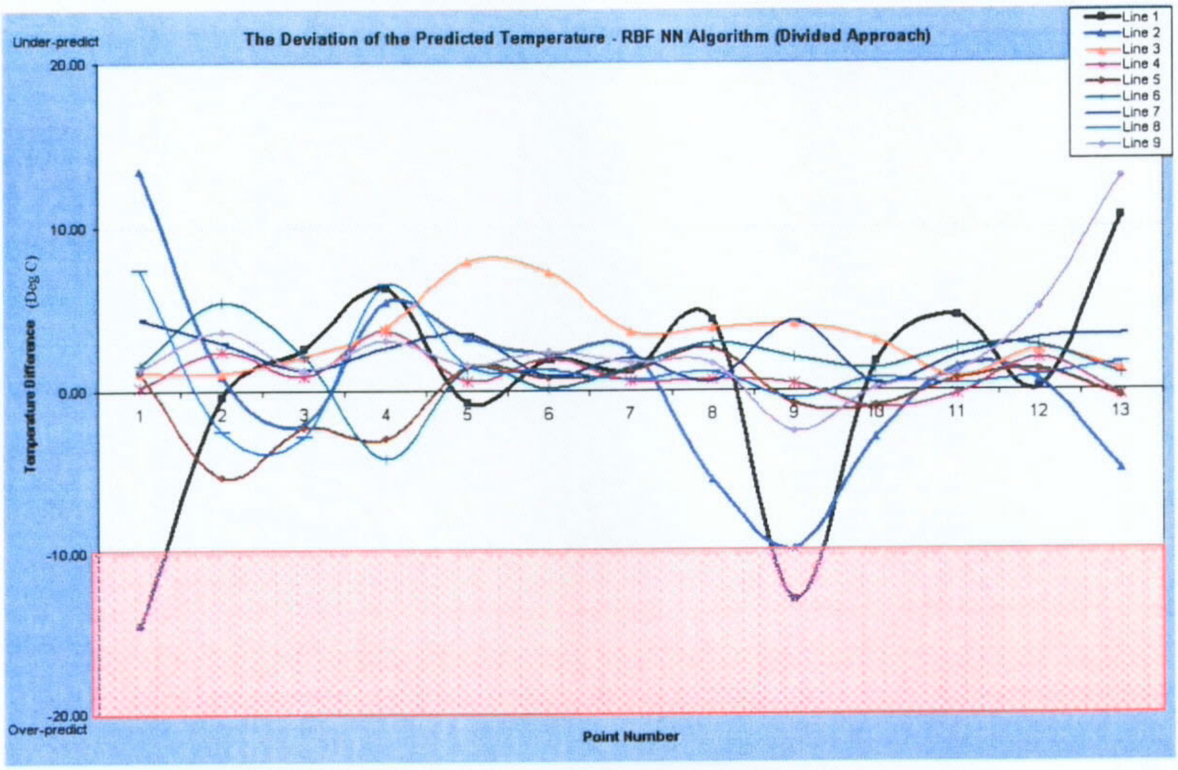


Fig. 52 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(RBF with Divided Approach)

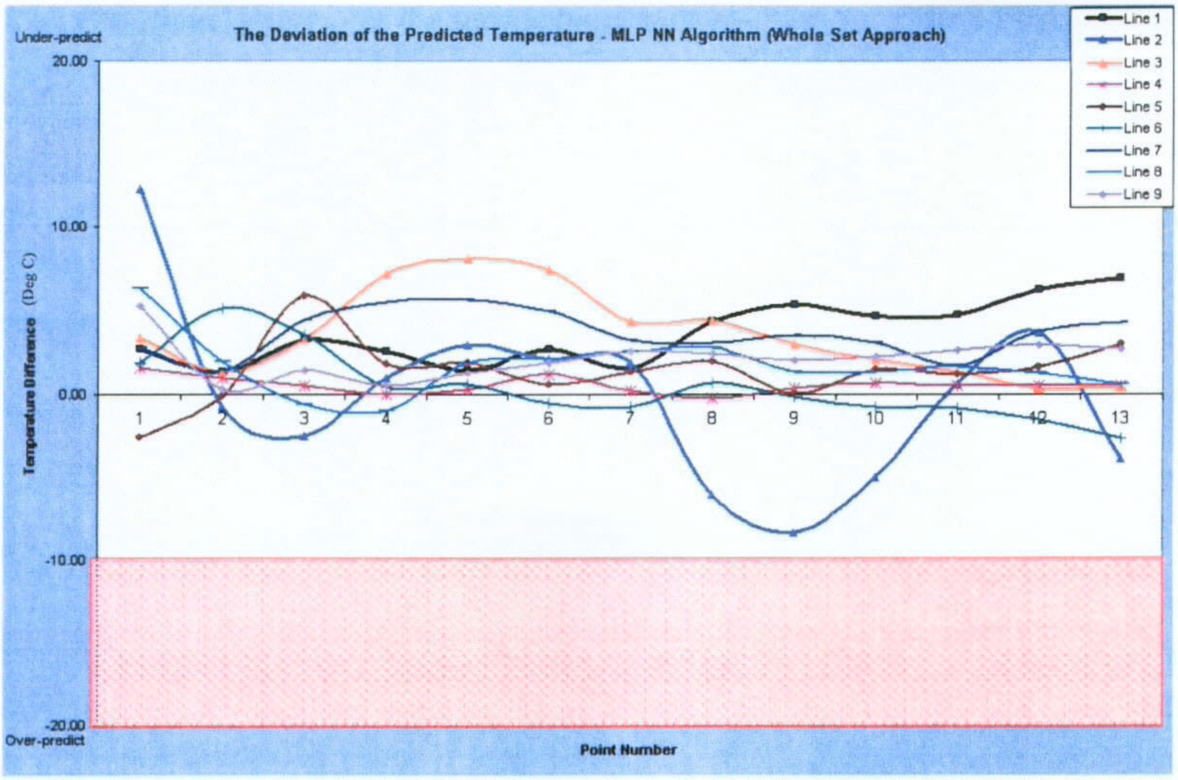


Fig. 53 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(MLP with Whole Set Approach)

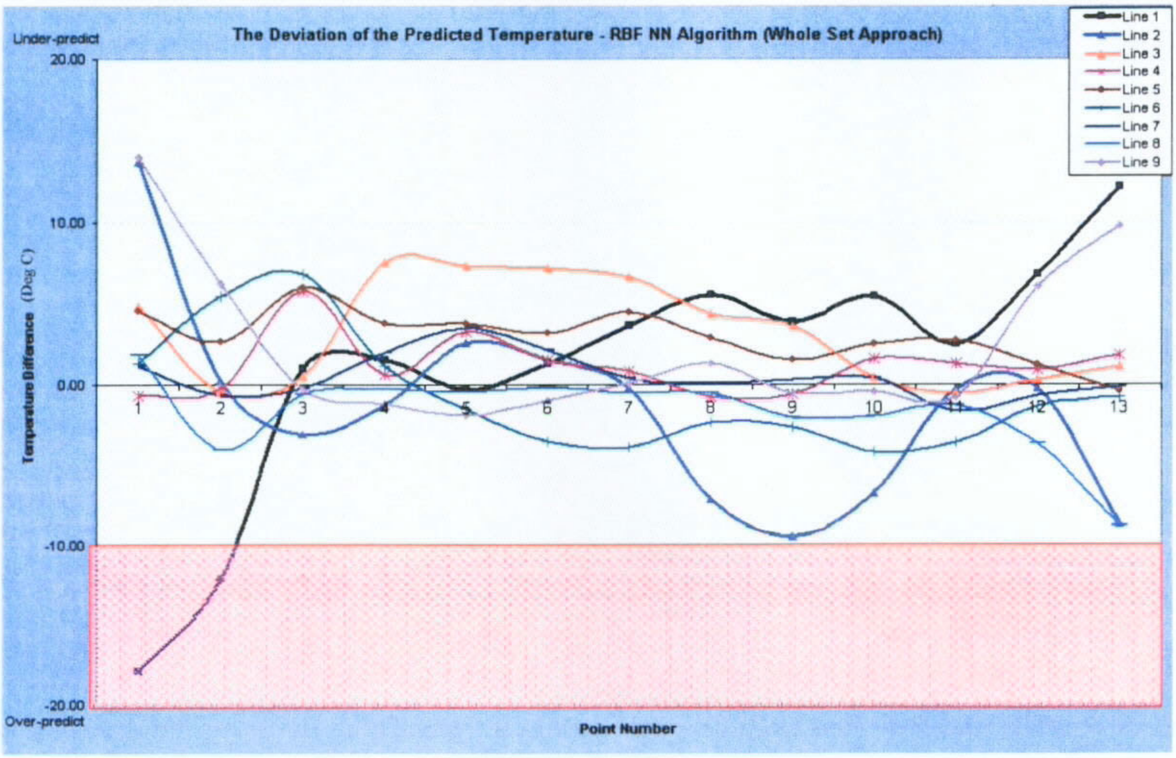


Fig. 54 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(RBF with Whole Set Approach)

5.2.2 Prediction Accuracy of the Second Investigation – New Style/Multi Model

In the second investigation, the prediction of an entirely new toaster case design, two different knowledge databases has been developed (i) data from different toaster models with only normal size, and (ii) data of toaster models with different sizes. The temperature predictions of a toaster case design from both MLP and RBF are shown in Figures 55 to 58 whilst the variation of the prediction temperature, the sizes of data sets, the required NN training times and sizes of the KIC database were summarized and listed in Table 12.

Similarly to the first investigation, any predicted results exceeded the preset limit (-10°C) were rejected. It was found that only the MLP with 1,872 (multi models and sizes) data sets could pass the criteria and no under prediction was occurred. The multi-model and sizes KIC system gave a maximum deviation of 19.87°C and a standard deviation of 6.41. It evidenced that the performance of the ANN with multi-model and size can give a satisfactory performance in predicting an entirely new style of toaster case. From literacy, these amounts of data that required to training the MLP properly is around 2000-3000 and the result could explains the amount of data input must large enough, so that the behavior of a prediction can be represented. As a result, a predefined design type with all different size of data included can predict different type of toaster design. Based upon the about two issues, it was concluded that the temperature prediction made by the MLP was far better than RBF in handling the heating test either in different size or in different style/shape of a new toaster design.

Table 12 Summary of the Temperature Results from Line 1 to Line 9 (Study 2)

	Max Temperature Difference (1872 data sets)				Max Temperature Difference (468 data sets)			
	MLP (Maximum Temperature Difference)	No of point out of Limit (T°C>-10)	RBF (Maximum Temperature Difference)	No of point out of Limit (T°C>-10)	MLP (Maximum Temperature Difference)	No of point out of Limit (T°C>-10)	RBF (Maximum Temperature Difference)	No of point out of Limit (T°C>-10)
Line 1	14.17	0 out of 13	-11.10	2 pts over predicted and exceed preset limit (reject)	-24.37	2 pts over predicted and exceed preset limit (reject)	15.41	0 out of 13
Line 2	13.58	0 out of 13	-13.77	3 pts over predicted and exceed preset limit (reject)	-14.75	3 pts over predicted and exceed preset limit (reject)	17.61	0 out of 13
Line 3	13.58	0 out of 13	-14.75	7 pts over predicted and exceed preset limit (reject)	-18.88	3 pts over predicted and exceed preset limit (reject)	-16.54	7 pts over predicted and exceed preset limit (reject)
Line 4	18.54	0 out of 13	-15.11	5 pts over predicted and exceed preset limit (reject)	-7.44	0 out of 13	-14.05	4 pts over predicted and exceed preset limit (reject)
Line 5	12.15	0 out of 13	24.94	2 pts over predicted and exceed preset limit (reject)	-11.28	2 pts over predicted and exceed preset limit (reject)	20.03	4 pts over predicted and exceed preset limit (reject)
Line 6	14.13	0 out of 13	-16.15	2 pts over predicted and exceed preset limit (reject)	-6.58	0 out of 13	-20.91	6 pts over predicted and exceed preset limit (reject)
Line 7	12.04	0 out of 13	-22.92	8 pts over predicted and exceed preset limit (reject)	10.06	0 out of 13	-19.99	8 pts over predicted and exceed preset limit (reject)
Line 8	19.51	0 out of 13	-21.23	10 pts over predicted and exceed preset limit (reject)	15.08	3 pts over predicted and exceed preset limit (reject)	-26.40	8 pts over predicted and exceed preset limit (reject)
Line 9	19.87	0 out of 13	-29.55	13 pts over predicted and exceed preset limit (reject)	15.21	0 out of 13	-27.42	6 pts over predicted and exceed preset limit (reject)
Total	100% Pass	Total 0 pt exceed within preset limits	Failed	Total 153 pts over predicted and exceed preset limit	Failed	Total 13 pts over predicted and exceed preset limit	Failed	Total 46 pts over predicted and exceed preset limit
No of Training Data	1872		1872		468		468	
Training Time (mins)	1320		1260		444		402	
Size of Database (Mbytes)	2.5		2.5		1		1	

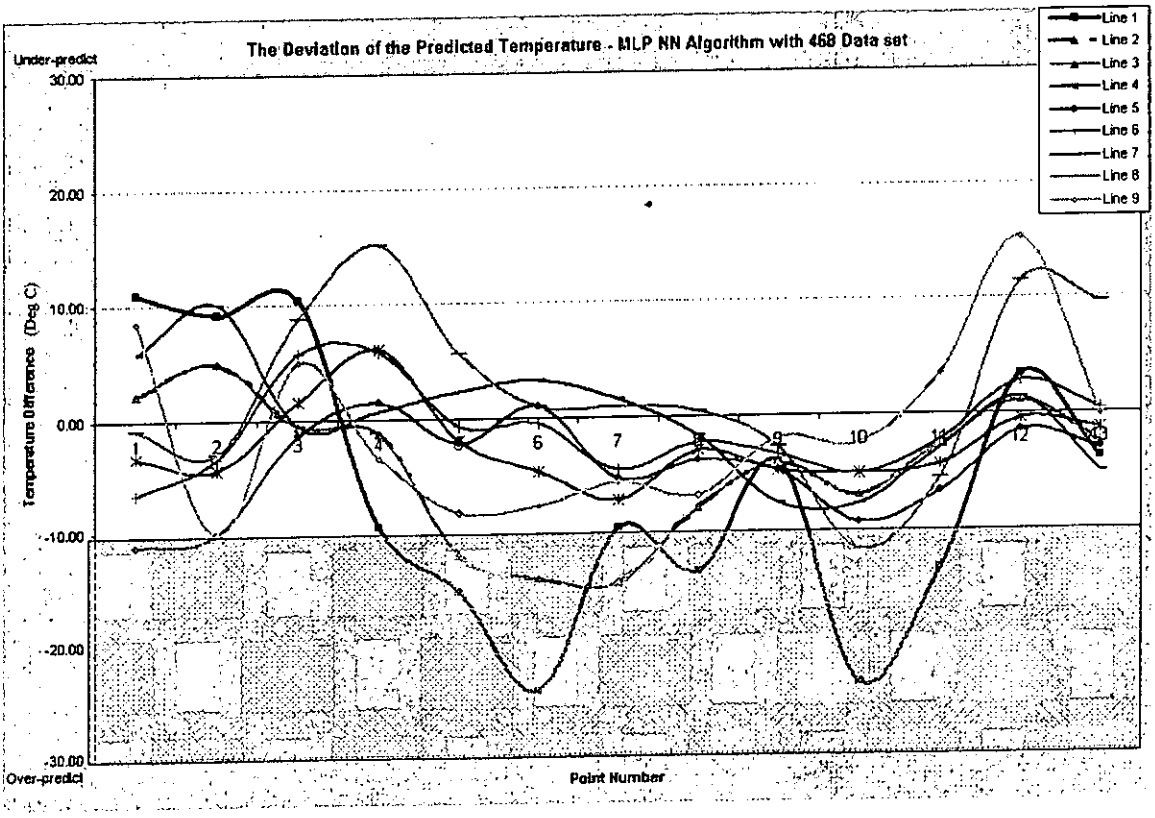


Fig. 55 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(MLP with Single Layer Approach)

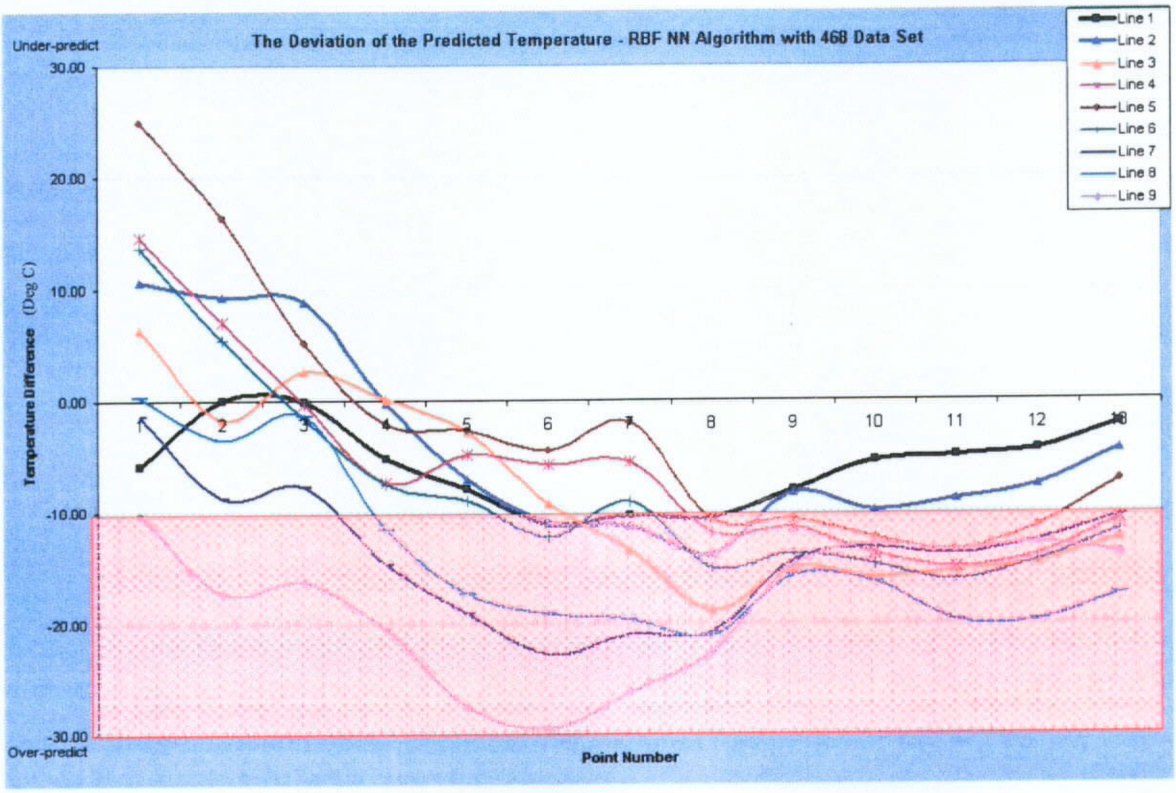


Fig. 56 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(RBF with Single Layer Approach)

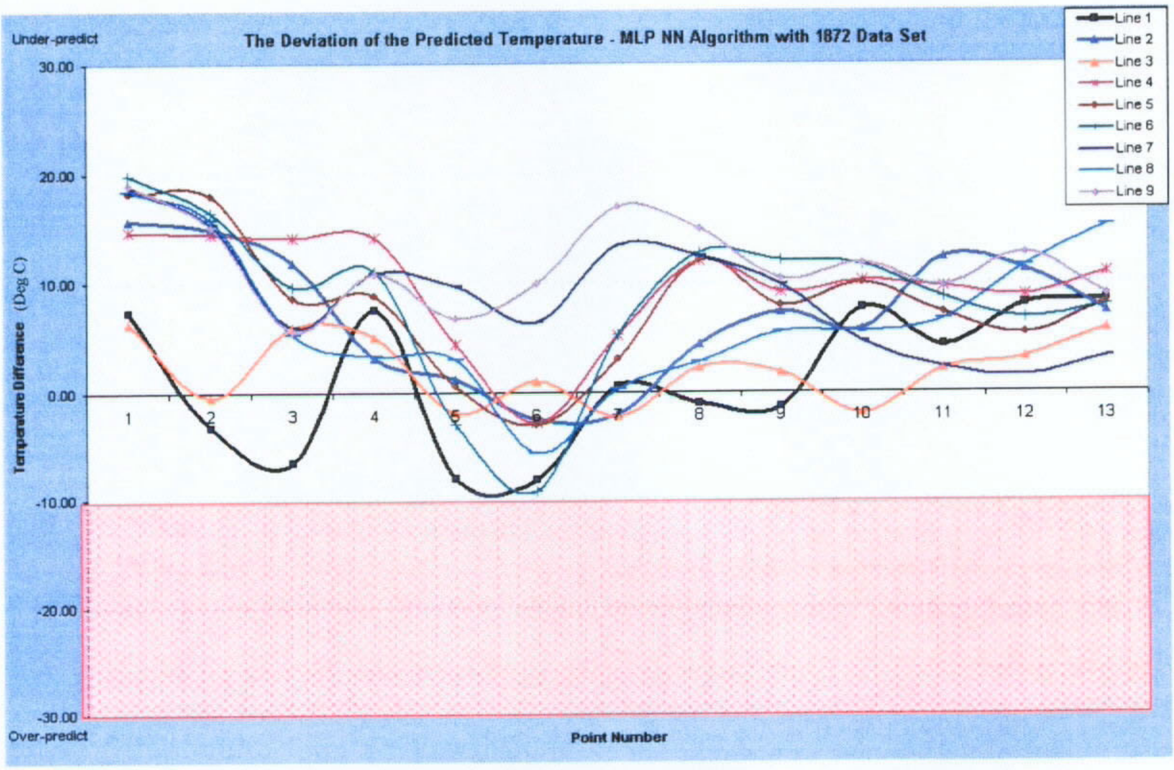


Fig. 57 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(MLP with Multi-Layer Approach)

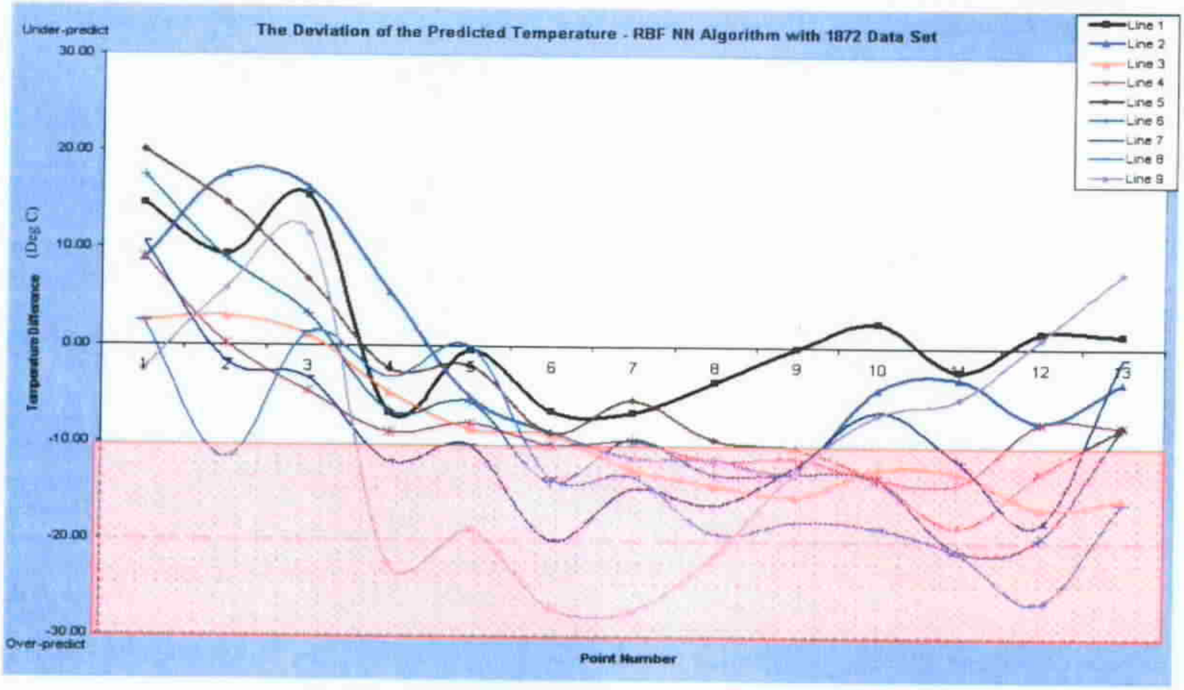


Fig. 58 Deviation of the Predicted Temperature Result from Line 1 to Line 9

(RBF with Multi-Layer Approach)

For the knowledge database that created in the second study, the temperature predictions for the second new toaster case with both MLP and RBF are shown in Fig. 59 to 60 respectively whilst Table 13 summarized their temperature prediction deviations. The MLP gave a maximum temperature deviation of 19.88°C and a standard deviation of 5.22 and the prediction had been improved by 9% for maximum and 18.56% for standard deviation (Fig. 61). The MLP with 1,989 data sets gave 7.17°C testing error (Table 11) and the network's performance improved as the number of data sets increased. When developing a neural network, one crucial and difficult to determine parameter is the number of neurons in the hidden layers. The hidden layer is responsible for internal representation of the data and the information transformation input and output layers. If the number of neuron is too few in a hidden layer, the network may not contain sufficient degrees of freedom to form a representation. If the number of neuron is too many, the network might get over-trained. Therefore, an optimum use for the number of neurons in the hidden layer is critical. In the second investigation, three different number neurons were used for training. Fig. 61 to 63 show the training results of the standard deviation, testing error and normal distribution for the different model predictions by using MLP and RBF algorithms. It was found that when the number of training data set increases up to 2000 in MLP, then the accuracy of the prediction will steadily increase that confirmed the most desirable size for training MLP is around 2000 sets. Contradictory, when the number of training data set increases, the accuracy of the RBF prediction also decreases. Fig. 64 shows when the number of training data set increases, the spread of MLP predictions becomes narrower and the confidence level increases. To sum up, the use of MLP with the whole set approach and sufficient training data sets can handle a multi-discipline/non-linear design problem that similar to the heat test. Also, if a company used the ANN technology to tackle similar design problem, confidence level and the data set availability are the critical factors in the selection of the appropriate ANN algorithm.

Table 13. Summary of the Temperature Predictions from Line 1 to Line 9 for the Confirmation Study

	Max Temperature Difference			
	MLP (Maximum Temperature Difference)	No of point out of Limit (T°C>10)	RBF (Maximum Temperature Difference)	No of point out of Limit (T°C>10)
Line 1	8.35	0 out of 13	17.38	0 out of 13
Line 2	15.7	0 out of 13	21.20	0 out of 13
Line 3	6.30	0 out of 13	-14.84	1 pt over predicted and exceed preset limit (reject)
Line 4	14.66	0 out of 13	24.35	0 out of 13
Line 5	18.11	0 out of 13	24.01	0 out of 13
Line 6	19.88	0 out of 13	25.11	0 out of 13
Line 7	18.59	0 out of 13	24.29	0 out of 13
Line 8	18.32	0 out of 13	20.41	1 pt over predicted and exceed preset limit (reject)
Line 9	18.89	0 out of 13	27.48	0 out of 13
Total	100 % Passed	Total 0 pt exceed within preset limits	Failed	Total 2 pts over predicted and exceed preset limit
No of Training Data	1,989		1,989	
Training Time (mins)	1,402		1,325	
Size of Database (Mbytes)	3.2		3.2	

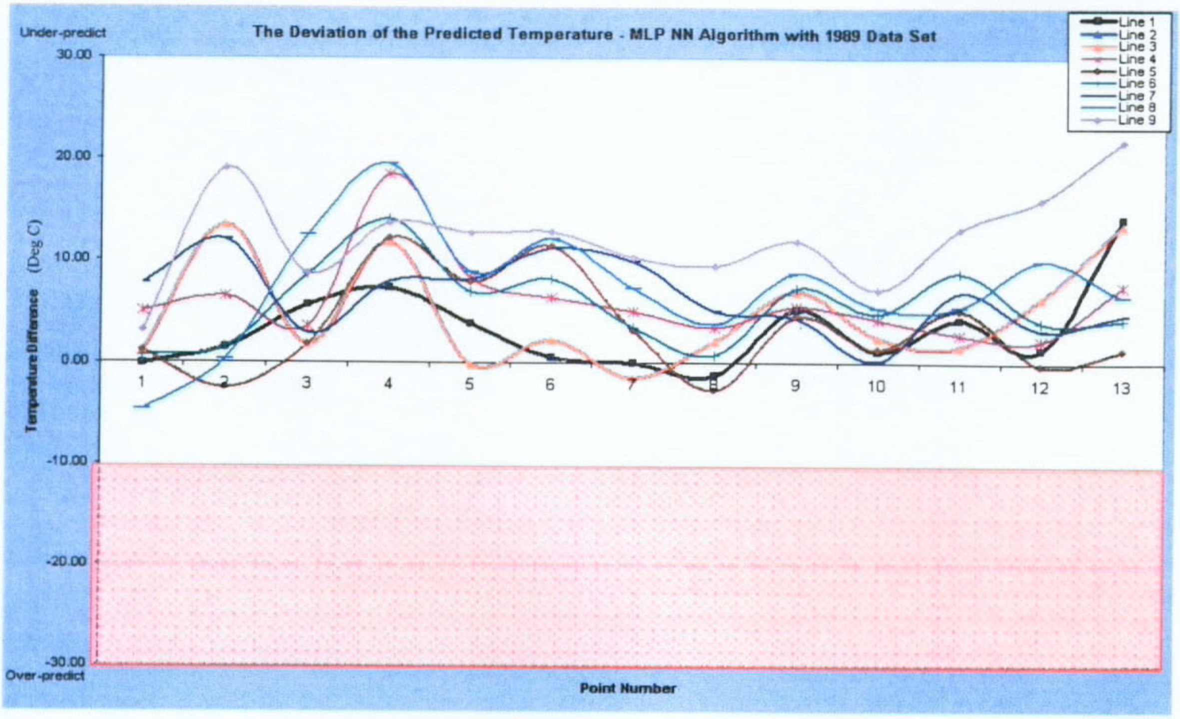


Fig. 59 Deviation of the Predicted Temperature Result from Line 1 to Line 9 of Confirmation Study (MLP)

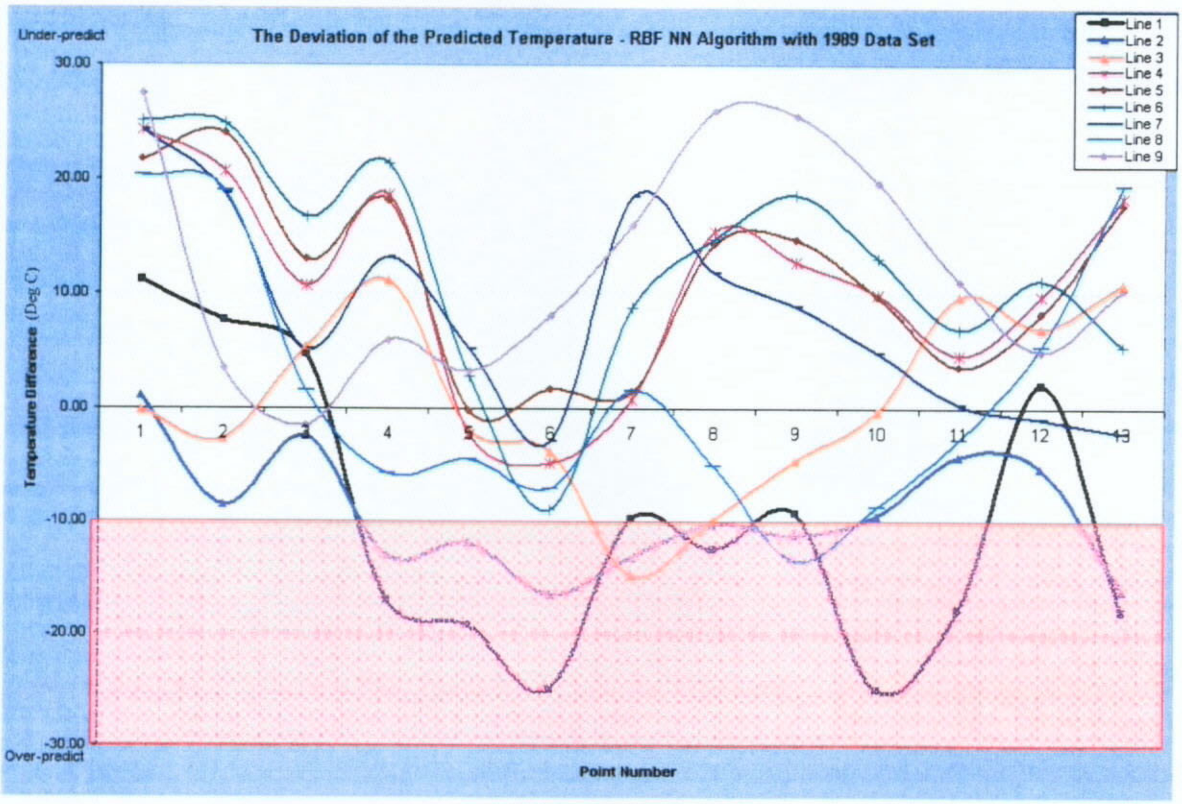


Fig. 60 Deviation of the Predicted Temperature Result from Line 1 to Line 9 of Confirmation Study (RBF)

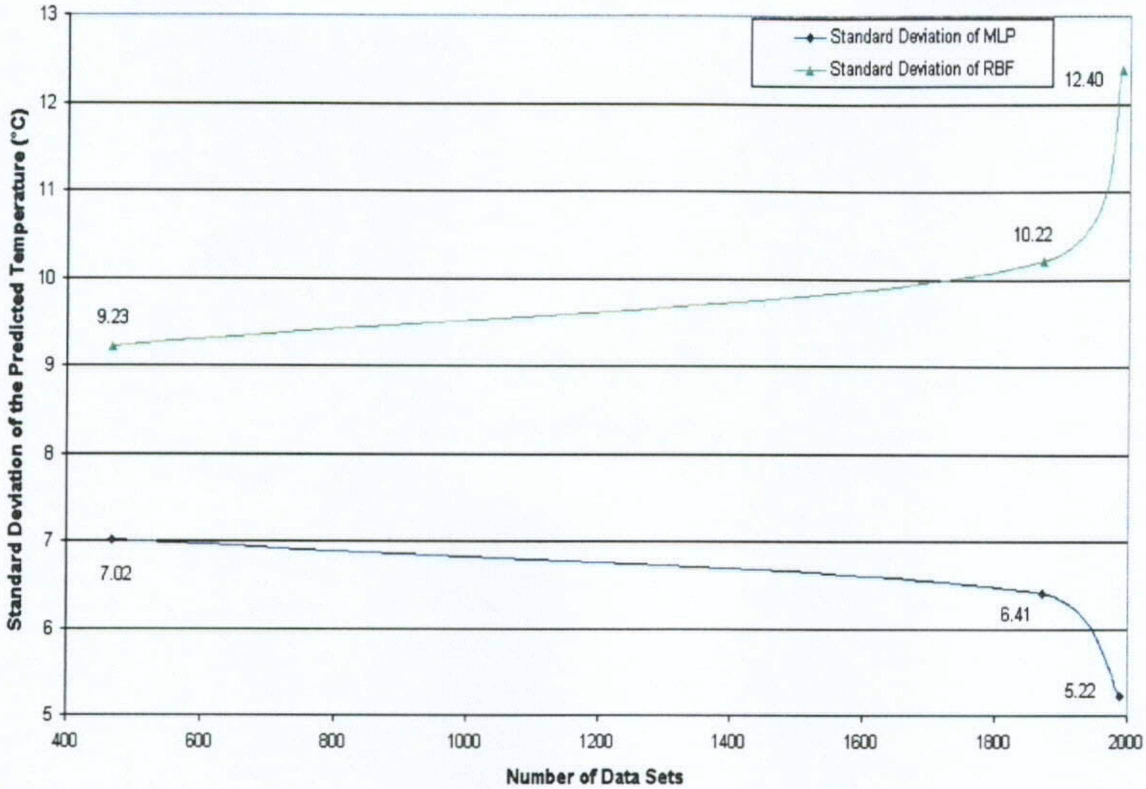


Fig. 61 Sensitivity of Training Data Set

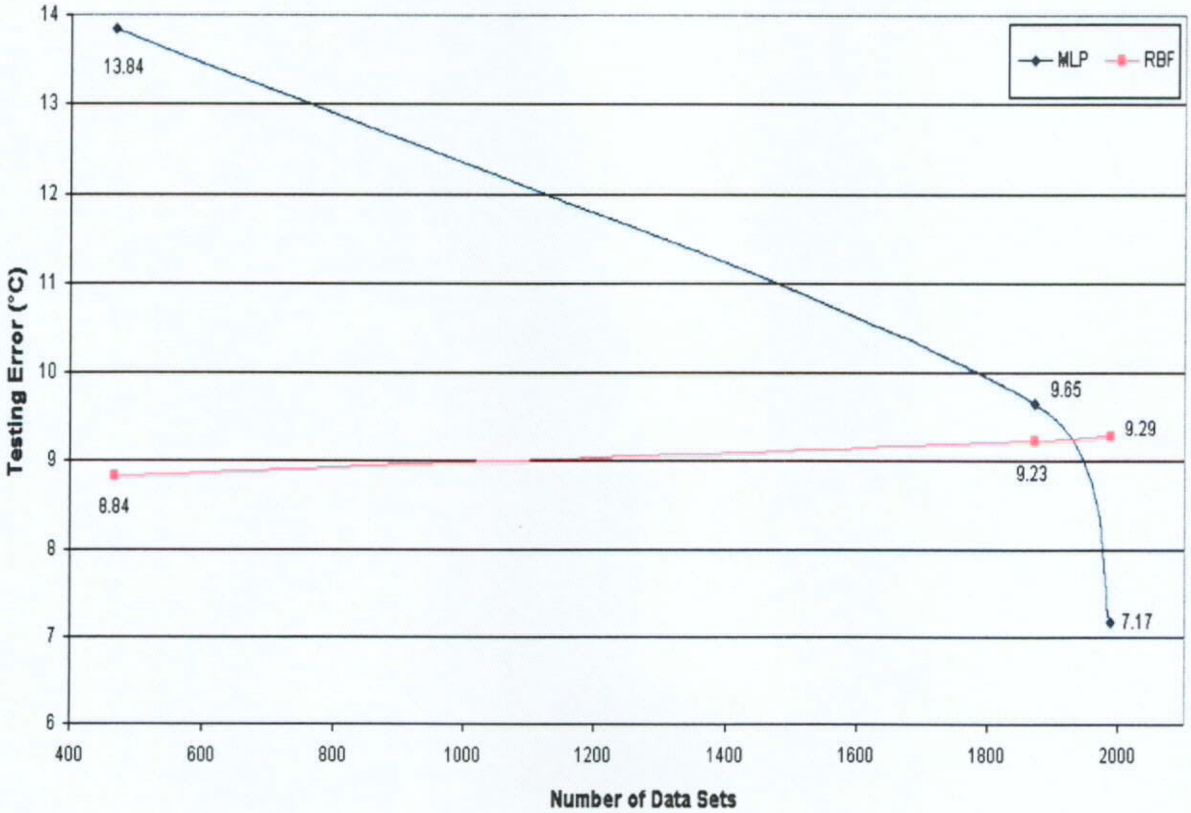
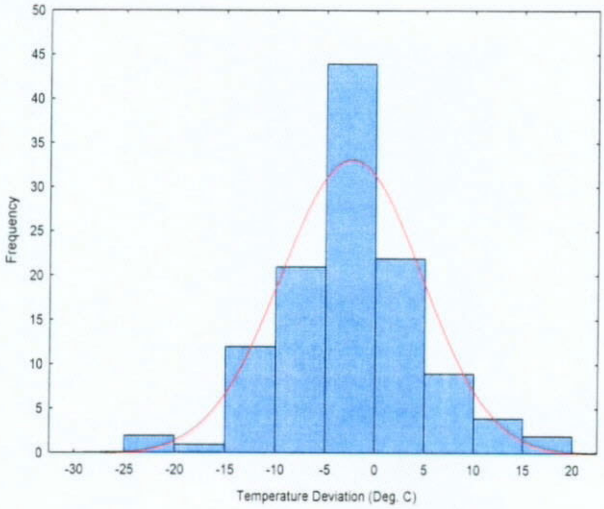
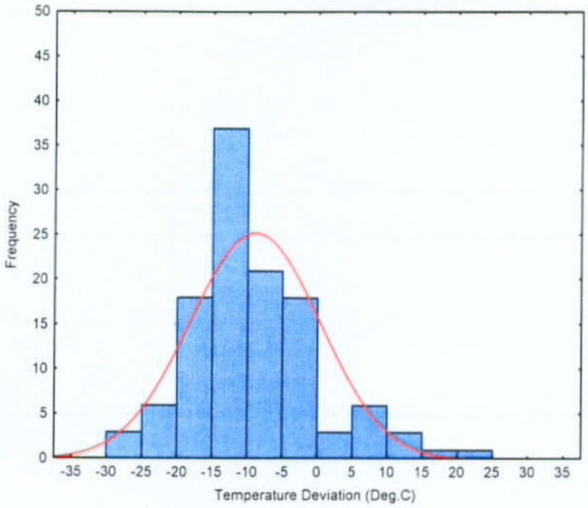


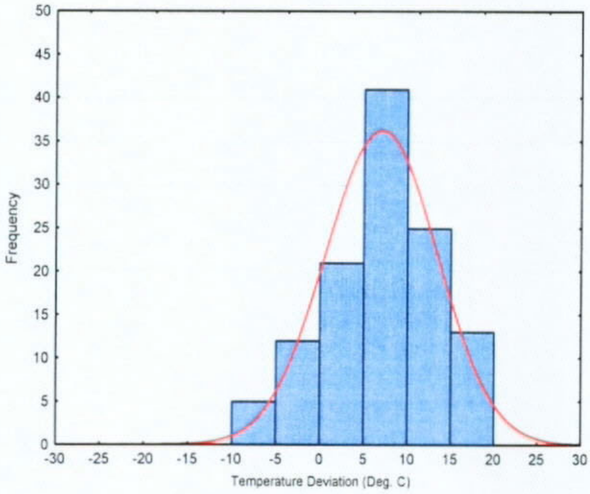
Fig. 62 Sensitivity of Training Data Sets



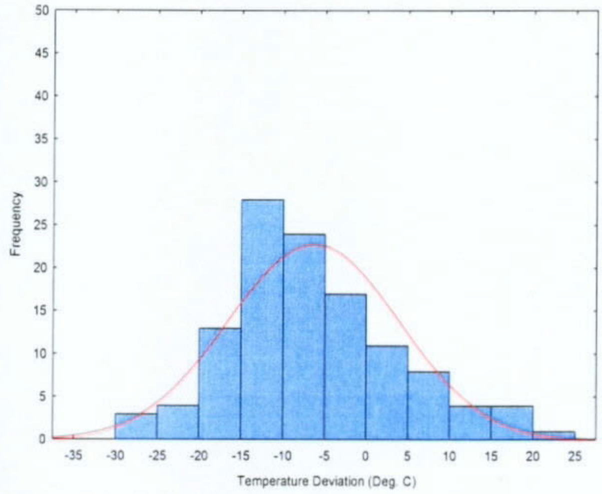
(a) MLP in 468 Training Data



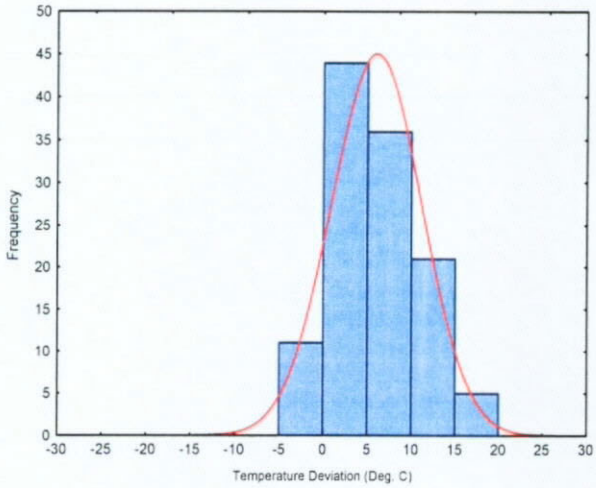
(b) RBF in 468 Training Data



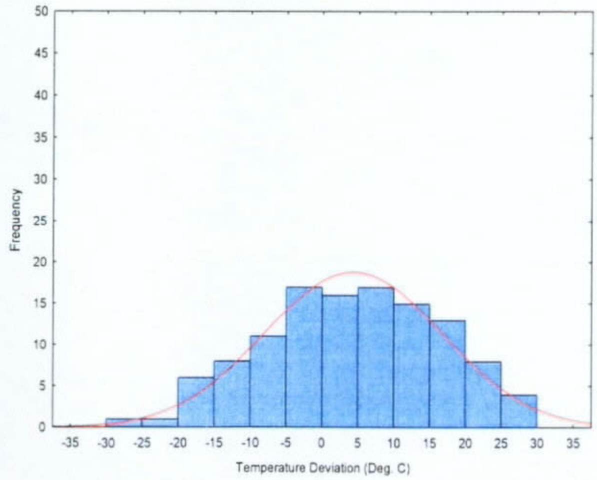
(c) MLP in 1872 Training Data



(d) RBF in 1872 Training Data



(e) MLP in 1989 Training Data



(f) RBF in 1989 Training Data

Fig. 63 Normal Distribution of the MLP and RBF with Different Number of Training Data Sets

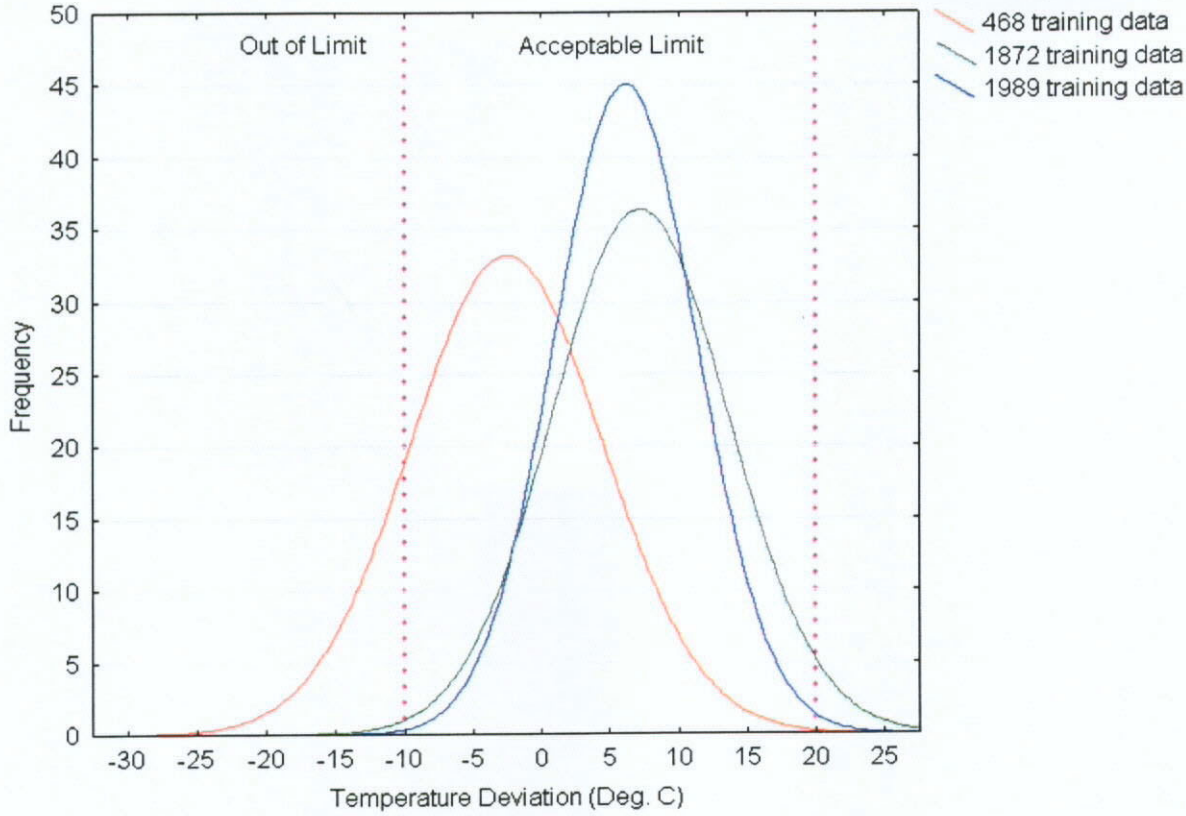
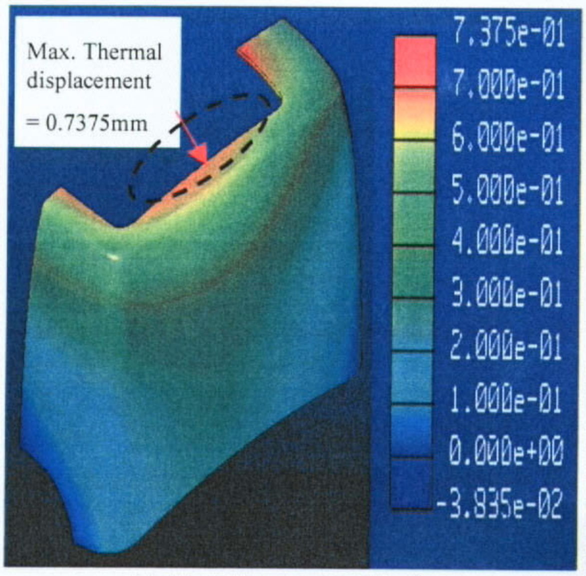


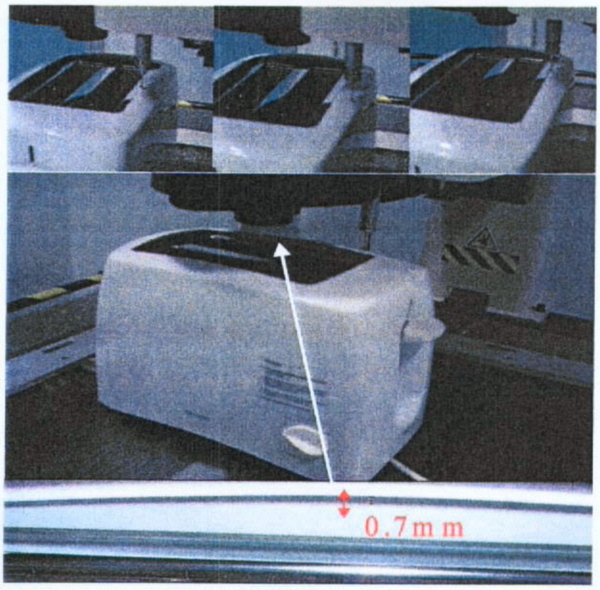
Fig. 64 Normal Distribution of Difference Number of Training Data Sets

5.2.3 Prediction of Thermal Displacement

Apart from temperature distribution prediction, the output of proposed KIC system can also be transferred as boundary conditions for the execution of a virtual experiment for the prediction of thermal displacement. The prediction of thermal displacement of the second toaster case design ranged from 0.6 mm to a maximum of 0.735 mm at the central top portion as indicated in Fig. 65a. By means of a coordinate measuring machine (CMM), nine points in the toaster case were measured and the thermal displacement ranged from 0.5mm to a maximum of 0.7mm (Fig. 65b). The thermal displacements between the virtual validation and actual toaster case were listed in Table 14. The deviations of the prediction and the actual thermal displacement were around 4% in average and 5% maximum. To conclude, by making use the temperature prediction from the KIC system as the boundary conditions for further validation, only a 5% maximum error was detected.



(a) By Virtual Validation



(b) By CMM

Fig. 65 Thermal Displacement Measurement of a Toaster Case

Table 14 Thermal Displacement Comparison between Virtual Validation and Actual

	Thermal Displacement Predicted by Virtual Validation (mm)	Actual Thermal Displacement Measured by CMM (mm)
Point 1	0.600 (Minimum)	0.580 (Minimum)
Point 2	0.665	0.638
Point 3	0.690	0.660
Point 4	0.715	0.685
Point 5	0.735 (Maximum)	0.700 (Maximum)
Point 6	0.720	0.688
Point 7	0.703	0.665
Point 8	0.674	0.650
Point 9	0.655	0.635
Point 10	0.631	0.620
Mean	**0.6788**	**0.6521**

5.3 Impact of the Proposed KIC System

The traditional toaster design process presents two interesting issues. Firstly, the new toaster products often have a similar shape with complex relationship of multi-discipline non-linear design behavior. Secondly, the design process is very time consuming and fraught with uncertainty when it is based on iterative improvement. This trial and error feedback loop in design needs to be eliminated by improving a structural analysis. The current product design process is iterative where mock up or prototype must be built and tested for their performance on applicable quality measures prior to final design. Since product design quality is becoming a competitive edge for a company, it needs to circumvent this trial and error process without sacrificing quality. For the current toaster design and development process (Fig. 66) of the partnered company, verification always takes place after the completion of a detail design. It is a normal practice that several iterations are required to take in order to fine-tune a design to meet all the necessary functional requirement tests. The time that required spending to confirm a new plastic toaster design case usually takes thirty-six days minimum. The proposed KIC system was brought to replace the traditional validation process and the time required to complete the validation of a heating test alone only takes one working day. The total time that usually requires to complete a new toaster case design, normally two trails have to be taken for heating test that can be reduced from 36 days to 14 days (2 days for heating test and 12 days for other tests) (Fig. 67).

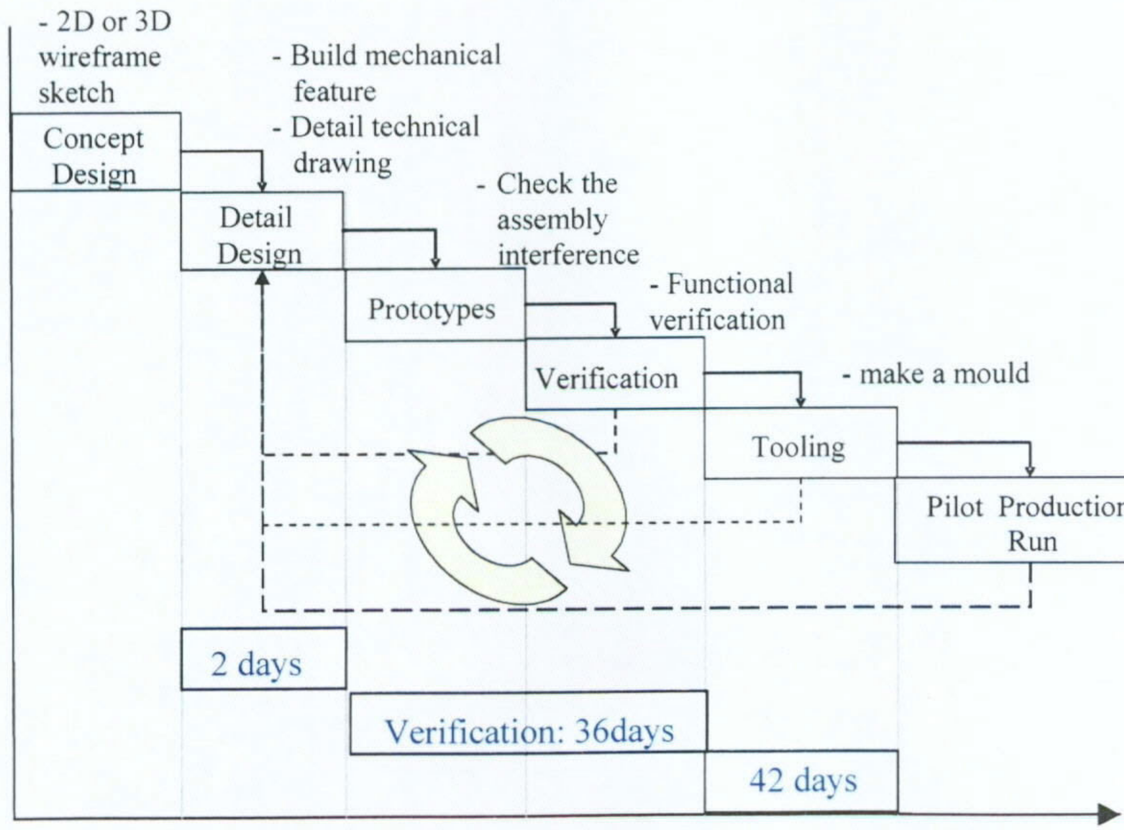


Fig. 66 The Traditional Toaster Development Process

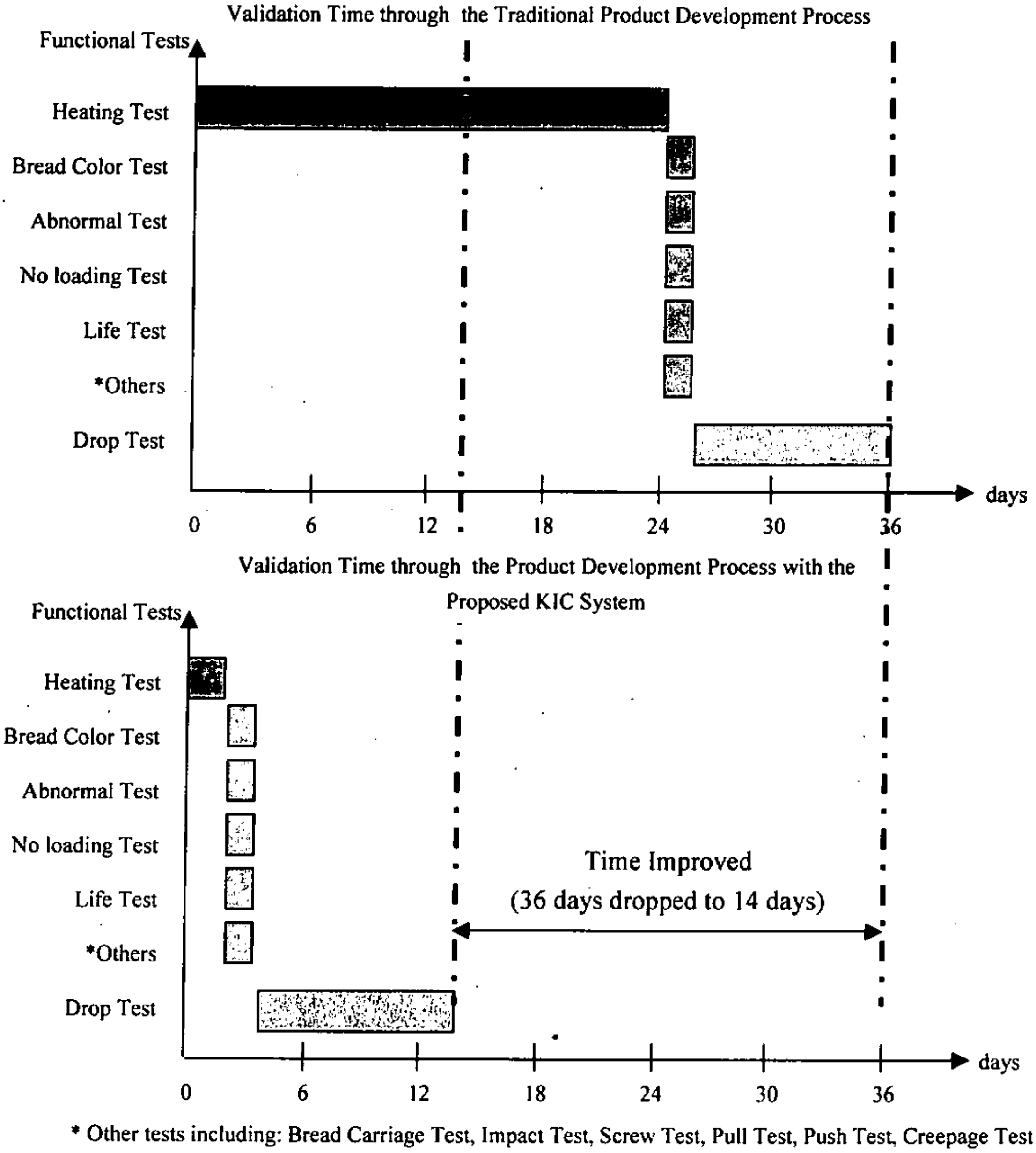


Fig. 67 The Validation Time between the Traditional Product Development Process and Proposed KIC System

By comparison with the traditional development time and the proposed KIC system, the total time compression for the toaster product validation was 61% ([(36-14)/36] *100%). Since heating test is the first KIC modules to address the proposed methodology, and similar validation modules such as drop test and bread color test can be applied to do so in a way. Therefore, the total expected reduction of product development time could be up to

89% ([(22+10)/36]*100%) after the completion of the drop test KIC module (bread colour test will be performed concurrently).

The KIC development cost consists of four components that include: (i) acquisition cost of an artificial neural network software, (ii) development cost of the graphical interfaces for input and output, (iii) development cost of the application programs, and (iv) the development cost of the data collection and conversion program. The price of a commercial neural network software ranges from US$500 to US$3,000 (Fig. 68). In this research, the investment of the ANN algorithm was only one thousand US dollars and the total development cost was forty-three thousand Hong Kong dollars (Table 15). When compare with the annual spend for a heating test (total expenditure 48 x HK$25000 x 2 = HK$2,400,000), the total development cost of the KIC system only accounts less than 2%. In comparison with the CAE software investment for solving multi-discipline non-linear design problems, the saving will be more significant. In a nutshell, the use of KIC not only speed up the design process but it also saves a lot of resources and enables the product design and development process lean. Furthermore, the KIC system can entertain new inquires and helping senior management to response quick/agile to its customer.

Fig. 68 The Price of the Commercial Neural Network Software Package

Table 15 The Investment Cost of the KIC Development

Item		Cost (HK dollar)
Neural Network Software	$US 1000 x 7.8	$7,800
User Interface Development Cost	88 (hrs) x $100	$8,800
Application Program Interface Development Cost	120 (hrs) x $100	$12,000
Data Extraction Program Development Cost	144 (hrs) x $100	$14,400
Total Investment Cost for Developing of KIC System		**$43,000**

5.4 Technical Barriers in the Developing a KIC System

Based on the research project, it was found that there existed three technical barriers in developing a KIC system that include: (i) understanding/identification of the AI/ANN algorithm characteristics, (ii) set up hypothesis/schema of training, and (iii) knowledge for the development of interfacing programs.

There are many different ANN algorithms available in the market and very few literacy talks about the applications of the ANN algorithms in any particular design problem. The research student had to spend a huge effort to understand the ANN algorithms and select the most appropriate ANN algorithms.

As mentioned before, the performance of a KIC system relies on the quality of the training data sets. Several reworks had been done in capturing accurate experimental data as some of the uncertainties have not been notified that included placement of the thermal couple and insertion depth, the joining of thermal couple and ventilation of the room. To solve them, a fixture was made to ensure the thermal couple could reach to the right positions and depths. In addition, as the connection of the thermal couple causing the different sensation of the temperature, all connected regions of the thermal couples need to be cut off and re-weld to ensure the best connection. Since the openings in a toaster case will affect airflow that will influence the data accuracy, with the fixture, all readings can be taken in the same locations.

As the development of the KIC system includes many interfaces between different programs, programming skills included Java, C++ seem to be the prerequisite. It causes a heavy workload in fulfill the programming needs.

Chapter 6 Conclusion and Recommendations for Future Development

6.1 Conclusion

Manufacturing companies in the Hong Kong electrical family appliance industry are now facing a critical challenge to shift up their business mode from OEM to ODM in order to continue their survival. Retain and deploy of knowledge are the most significant successful factors in such migration. In this project, a KIC system was proposed and illustrated to solve a particular design application for the development of a plastic new toaster case. The missed gap in between the correctional sequential product development and the use of fully computer aided product development is proved can be bridged with the knowledge intensive CAD technology. Through the deployment of the KIC technology, legacy data of a particular application can be crystallized to form a knowledge database, so that explicit knowledge can be transformed to tacit knowledge for future application. The roadmap for the development of a KIC system had been established by considering the small electrical family appliance industry's operating environment as well as the available AI/ANN technology and resource of a manufacturing company. This research had not only developed a structural methodology for problem disassociation, but also has provided a mechanism for mapping the feature s of a design problem to a suitable AI/ANN algorithm together with a monitoring procedure for the ANN training process to avoid overfitting. The project did not just demonstrate the feasibility of using KIC but also provide evidences, it is an affordable solution for the small electrical family appliance industry for the enhancement of its design competence and aids the product migration to middle and high-end consumer market. Through the development of the KIC system prototype to solve the heating test problem, it was demonstrated that a multi-discipline/non-linear design problem could be solved in such a way. With a performance comparison between the traditional validation process and the KIC methodology, it was evidenced that accuracy, processing time and costs required for the KIC methodology/study gave very satisfactory results. Even through there are still plenty of room for further development, it was very exciting to learn that the partnered company will continue the development of their KIC system and expect to develop their knowledge intensive process design for the company's injection molding operation.

6.2 Recommendations for Future Development

In fact, much further work can be done for improving the effectiveness of the KIC system. Further development recommend include selection and training of the ANN algorithm, and determination of the optimum training data set.

(i) In the KIC development roadmap, the selection of the best ANN algorithm was done by comparing all the predictions and based on the best results for the final schema selection. Such trail and error approach is very time consuming and thus further research should be correct onto develop a deductive ANN selection mechanism so that the identification process should be improved and speeded up. In addition, in the training process of the ANN algorithm, the optimum hidden layer and neuron weight were determined by the rebound of the verification errors. Further investigation might include the study of a genetic algorithm to compare the prediction performance.

(ii) In the second investigation, the optimum number of training data sets for a particular design problem had been determined. Further research studies are recommended to carry out to find out the amount of the optimum data set that required for a prediction for each ANN algorithm.

To fully develop a product design KIC system using the proposed methodology, it should be constructed with a high level language (such as C or Java) to link up and automate the process between the CAD system and AI/ANN technology during the crystallization and deployment process. This research has only developed the structure of a KIC system for the heating test. In order to fully assess the contribution of the proposed methodology, one can construct of the whole product development KIC system from design to process.

References and Bibliographies

1. Barens, *Statistical Neural Network Manual,* http://www.statsoftinc.com (2000).

2. Barr & Feigenbaum, "Heuristic State Space Search", *The Handbook of A.L*, Vol. 1, William Kaufmann, Los Altos, California, pp.58-63 (1981).

3. Beckman, T., "A Methodology for Knowledge Management", *AI and Soft Computing Conference*, International Association of Science and Technology for Development (IASTED), Banff, Canada, pp.29-32 (1997).

4. Beckman, T., *Knowledge Management Seminar*, ITESM, Monterrey Mexico, http://userpages.umbc.edu/~buchwalt/papers/KM10-FINAL.htm (1998).

5. Broomhead and D. Lowe, "Multivariable Functional Interpolation and Adaptive Networks", *Complex Systems 2*, pp.321-355 (1988).

6. Bryson and Y. C. Ho., *Applied optimal control*, Blaisdell, pp.121 (1969).

7. CIEC, China International Economic Consultants Ltd, *Outlook on China's Electrical Household appliance*, http://www.friedlnet.com/images/0009-017_contents.pdf (2001).

8. Dataware Technologies Inc., "Seven Steps to Implementing Knowledge Management in Your Organisation", *Corporate Executive Briefing*, http://www.dataware.com, (1998).

9. Davenport, T. and Probst, G., *Knowledge Management Case Book,* Publicis MCD Verlag and John Wiley & Sons, Munich, pp.11-26 (2000).

10. David Garson, "Neural Networks", *An Introductory Guide for Social Scientists*, SAGE Publication London, pp.23-27 (1998).

11. Department of Industrial and System Engineering, *Shaping the Future Design for Hong Kong,* Department of Industrial and System Engineering, Hong Kong Polytechnic University, pp.1-12 (2003).

12. Drucker, "The Coming of the New Organisation", *Harvard Business Review on Knowledge Management*, pp.1-30 (1998).

13. Drucker, P., "Knowledge Worker Productivity: The Biggest Challenge", *California Management Review*, Vol 40, No 2, pp.79-85 (1999).

14. Dyer, G., "KM Crosses the Chasm", *Knowledge Management Magazine*, http://www.destinationkm.com/articles/default.asp?ArticleID=170 (2000).

15. Farshad, F., J. Garber, and Juliet N. Lorde, "Predicting Temperature Profiles in Producing Oil Wells Using Artificial Neural Networks", *Engineering Computations*, Vol 17, No. 6 and 7, pp.735-754 (2000).

16. Fu L.M., "Knowledge-based Connectionism for Revising Domain Theories", *IEEE Transactions on Systems*, Man and Cybernetics, 23, pp.173-182 (1993).

17. Gamble, P. and Blackwell, J., *Knowledge Management A state of the art guide*, Kogan page, London, pp.5 (2001).

18. Geoffrey Hinchliffe, *The Integration of Skills and Knowledge*, http://www.herts.ac.uk/envstrat/HILP/conferences/ 2nd/PAPERS/Hinchliffe.doc

19. Ghoshal, S and Bartlett, C., *The Individualised Corporation: A Fundamentally New Approach to Management*, Harper Business, London, pp.1-68 (1998).

20. Grossberg, S., "How does a Brain Build a Cognitive Code", *Psychological Review*, 87, pp.1-51 (1980).

21. Grunstein, M. and Barthès J.-P., "Knowledge Management: Organization, Competence and Methodology", Proc. of ISMICK'96, Rotterdam, the Netherlands, Wurzburg:Ergon Verlag, *Advances in Knowledge Management*, Vol. 1, October 21-22, pp. 258-264 (1996).

22. Holsapple, C. and Joshi, K., "Knowledge Management: A Three-fold Framework", *Kentucky Initiative for Knowledge Management paper*, No.104 (1997).

23. Hong Kong Productivity Council, *Industry Study on Electrical Household Appliances*

Industry, Hong Kong Productivity Council, pp.5-6 (1998).

24. Hopfield, John J, "Neural Network and Physical System with Emergent Collective Computational Abilities", *Proceedings of the National Academy of Sciences*, USA, 79, pp.2554-2558 (1982).
25. John Petkov, *Statistical Neural Network Manual*, http://www.statsoftinc.com (2000).
26. Junnarkar, B. "Creating Fertile ground For Knowledge Management at Monsanto", *Perspectives on Business Innovations*, http://www.businessinnovation.ey.com/jouranl /issue1/features/creati/loader.html (1999).
27. Kandel, A. and Langholz, G., *Hybrid Architectures for Intelligent Systems*, Boca Raton, FL:CRC Press, http://citeseer.nj.nec.com/context/43360/0 (1992).
28. KMPG, *The Knowledge Journey: A business guide to knowledge systems*, KPMG Consulting, pp.1-6 (1998).
29. Kohonen, T., "Self-organized formation of topologically correct feature maps", *Biological Cybernetics*, 43, pp.59-69 (1982).
30. Kohonen T., *Self-Organizing Maps Springer Series in Information Sciences*, Vol. 30, Springer, Berlin, Heidelberg, New York, pp.1-20 (1995).
31. KPMG, *Knowledge Management Consultant Report,* KPMG Consulting, pp.1-6 (2000).
32. LeCun, Y., "A Theoretical Framework for Back-propagation", *Proceedings of the 1988 Connectionist Models Summer School*, D. Touretzky, G. Hilton and T. Sejnowski, eds, Morgan Kaufmann, San Mateo, Ca, pp.21-28 (1988).
33. Liebowitz, *Building Organizational Intelligence: A Knowledge Management Primer*, CRC Press, Boca Raton, FL, pp.1-160 (2000).
34. Liebowitz, J. and Beckham, T., *Knowledge Organizations: What Every Manager Should Know*, St Lucie/CRC Press, Boca Raton, FL, pp.1-208 (1998).
35. Lim, D and Klobas, "Knowledge Management in Small Enterprises", *Journal of*

Knowledge Management, Vol. 18, No 6, pp.420-432 (2000).

36. MacCallum K J, Duffy A H B and Green S, "The Knowledge Cube - A Research Framework for Intelligent CAD", *Int. Intelligent Computer Aided Design Workshop*, Boston, U.S.A, pp.38-44 (1987).
37. Mantyla M, "Knowledge Intensive CAD: Introduction and a Research Agenda", *Knowledge Intensive CAD*, pp.1-12 (1995).
38. Mantyla M, Susan Finger and Tetsuo Tomiyama, "Knowledge Intensive CAD II", *Proceedings of the IFIP TC5 WG5.2 International Conference on Knowledge Intensive CAD*, Pittsburgh, pp.3-295 (1996).
39. Marquardt, M., *Building the Learning Organisation*, McGraw Hill (1996).
40. Masaki Ishii, Tetsuo Tomiyama, Hiroyuki Yoshikawa, "A Synthetic Reasoning Method for Conceptual Design", *Towards World Class Manufacturing*, pp.3-16 (1993).
41. McCarthy, J., "Program with common sense", *Proceedings of the Symposium on Mechanisation of Throught Processes*, Vol.1, London, pp.77-84 (1958).
42. McCulloch, W.S. and Pitts, W., "A Logical Calculus of the Ideas Immanent in Nervous Activity", *Bulletin of Mathematical Biophysics*, 5, pp.115-133 (1943).
43. Minsky Marvin, and Seymour Papert, *Perceptrons*, Cambridge Ma: The MIT Press, pp.1-120 (1969).
44. Nelson, R.R. and Winter, S., *An Evolutionary Theory of Economic Change*, Cambridge, Harvard U.P, pp.1-67 (1982).
45. Nonaka, and Takuchi, *Knowledge Creating Company*, Oxford University Press, pp.96-104, (1995).
46. O'Dell, C., "A Current Review of Knowledge Management Best Practise", *Conference on Knowledge Management and the Transfer of Best Practices*, Business Intelligence, London (1996).

47. O'Dell, C. and Grayson, C.J., "If Only We Know What We Know: identification and transfer of internal best practices", *California Management Review*, Free Press, New York, Vol. 40 No. 3, pp.154-74 (1999).

48. Paker, D.B., "Optimal Algorithms for Adaptive Networks: Second Order Back Propagation, Second Order Direct Propagation, and Second Order Hebbian Learning", *Proceedings of the IEEE 1st International Conference on Neural Network*, San Diego, CA, Vol. 2, pp.593-600 (1987).

49. Pascarella, P., "Harnessing Knowledge", *Management Review*, pp.37-40 (1997).

50. Petrash, G., "Managing Knowledge Asset For Value", *Knowledge-Based Leadership Conference*, Linkage, Inc. Boston, http://courses.washington.edu/hs590a/modules/38/know38b.html (1996).

51. Quinn J B, Anderson P and Finkelstein S, "Managing professional intellect: making the most of the best", *Harvard Business Review*, March-April, pp.71-80, (1996).

52. Rosenblatt, F., *Principles of Neurodynamics*, New York: Spartan, pp.1-30 (1961).

53. Ruben Stein-Montano, "SMARTVision: a Knowledge-Management Methodology", *Journal of Knowledge Management*, Vol.5, no.4, pp.300-310 (2001).

54. Ruggles, *Tools for Knowledge Management: An Introduction (KM Tools)*, Butterworth-Heinemann, Oxford, pp.1-240 (1997).

55. Rumelhart D.E., *Parallel Distributed Processing: Explorations in the Microstructures of Cognition*, Vol. 2, MIT Press, Cambridge, MA http://citeseer.nj.nec.com/context/20499/0 (1986).

56. Senge, *The Fifth Discipline*, Random House Australia Pty Ltd, pp.1-424 (1990).

57. Specht, "A General Regression Neural Network", *IEEE Transactions on Neural Networks*, 2, pp.568-576 (1991).

58. Stewart, T., *Intellectual Capital: The New Wealth of Organizations*, Nicolas Bresley Publishing, London, pp.1-304 (1998).

59. Stewart, T., *The Wealth of Knowledge*, Nicholas Brealey Publishing, Foreword, pp.8, 125 (2001).

60. Suh, N. P., *The Principles of Design*, Oxford University Press, New York, pp.30-80 (1990).

61. Sutherland, I.E., "Sketchpad--A Man-Machine Graphical Communication System", *Proceedings of the Spring Joint Computer Conference*, Detroit, Michigan and MIT Lincoln Laboratory Technical Report, pp.296 (1963).

62. Tetsuo Tomiyama, K. P. Hew, "Knowledge Intensive Computer Aided Design: Past, Present and Future", *Knowledge Intensive CAD*, pp.3-18 (1998).

63. Tetsuo Tomiyama, Yasushi Umeda, Takashi Kiriyama, "A Framework for Knowledge Intensive Engineering", *CAST*, pp.123-147 (1994).

64. Thesaurus, *Oxford English Dictionary*, http://search.oed.com/ (1980).

65. Tiwana, A., *The Knowledge Management Toolkit*, Prentice Hall, NJ, pp.1-416 (2000).

66. Tobin, D.R., *Networking Your Knowledge*, Management Review, pp.46-48 (1998).

67. Tobin, D.R., *The Knowledge-enabled Organisation*, AMACOM, New York, http://www.knowledge.hut.fi/projects/itss/referTobin.pdf (1997).

68. Tomiyama and M. Mantyla, "Knowledge Intensive Computer Aided Design", *Proceedings of the IFIP TC5 WG5.2, International Conference on Knowledge Intensive CAD*, pp.3-321 (1998).

69. Tomiyama, T., Yoshikawa, H., "Extended General Design Theory in Design Theory for CAD", *Proceedings of the IFIP Working Group 5.2 Working Conference 1985 in Tokyo*, Yoshikawa, H., Warman, E.A. (eds.), North-Holland, Amsterdam, The Netherlands, pp.95-130 (1987).

70. Turban, E., *Expert System and Applied Artificial Intelligence*, New York: Macmillan Pub. Co., pp.1-80 (1992).

71. Van der Spek, R. and Spijkervet, A., "Knowledge Management: Dealing Intelligently

with Knowledge", in Liebowitz, J. and Wilcox, L. (Eds)., *Knowledge Management and its Integrative Elements*, CRC Press, Boca Raton, FL, ISBN 90-75709-02-1 (1997).

72. Warwick J. McKibbin, "The Consequences of China's WTO Accession on its Neighbours", *Seminar on Asian Competitiveness*, http://www.nber.org/cgibin/ author_papers.pdf, pp.1-2 (2002).
73. Wickert, A. and Herschel, R., *Knowledge-management issues for smaller businesses* Journal of Knowledge Management, Vol.5, no. 4, pp.329-337 (2001).
74. Wiig, K., *Knowledge Management Foundation - thinking about: how people and organizations create, represent, and use knowledge,* Schema Press, pp.1-45 (1993).
75. Woolf, H. ed., *Webster's New World Dictionary of the American Language*, G. and C. Merriam, pp.1-704 (1990).
76. Wurzburg, E., V., *Advances in Knowledge Management*, Vol. 1, October 21-22, pp.258-264 (1996).
77. Zadeh, L. *Fuzzy Sets' and Systems,* Proceedings of Symposium on System Theory, Polytechnic Institute of Brooklyn, pp. 29-37(1965).
78. Zamarreno, Vega, "Neural Predictive Control: Application to a highly Non-linear System", *Engineering Applications of Artificial Intelligence*, Vol. 2, pp. 149-158 (1999).

Appendix I - Results of the First Investigation

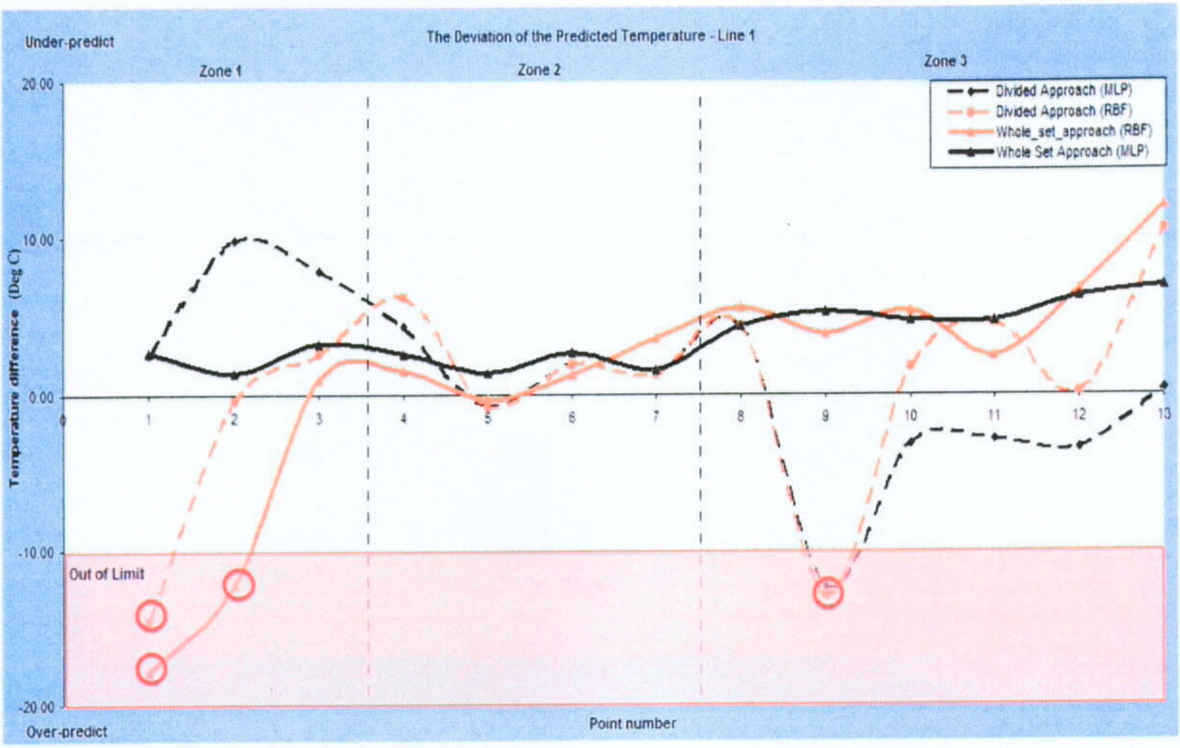


Fig. 71 Deviation of the Predicted Temperature of Line 1 in the First Investigation

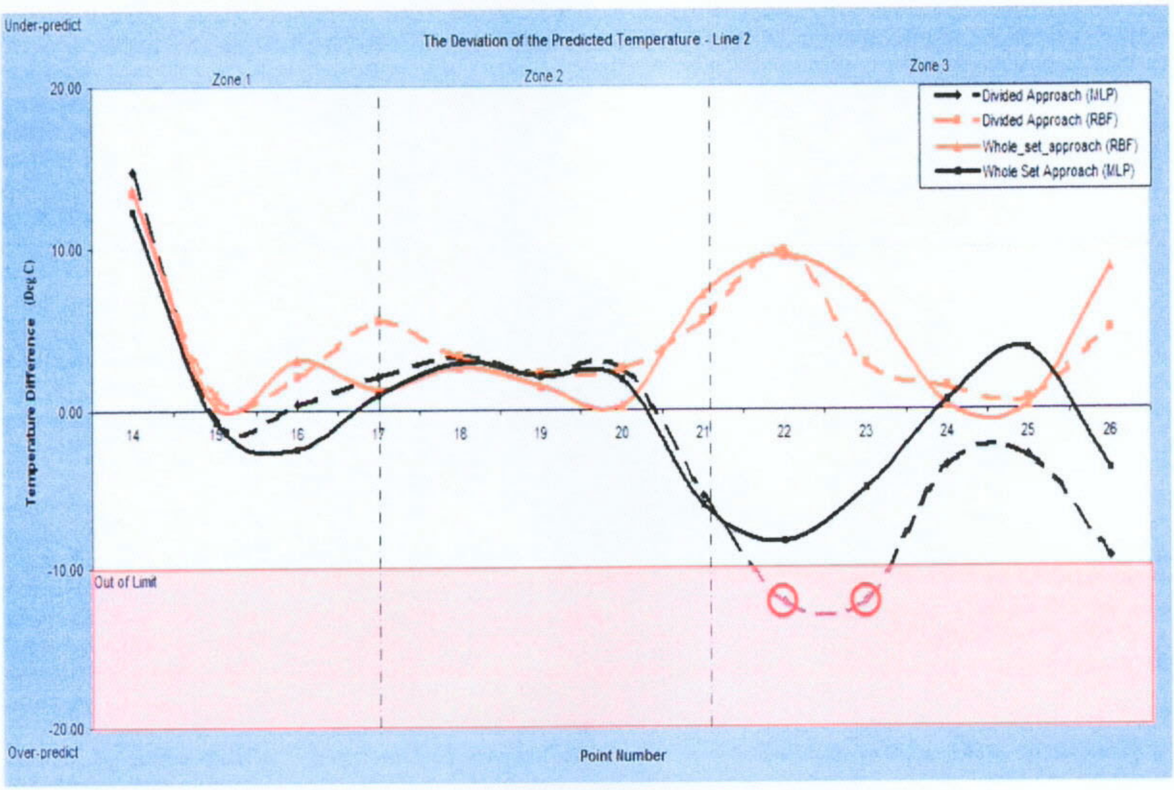


Fig. 72 Deviation of the Predicted Temperature of Line 2 in the First Investigation

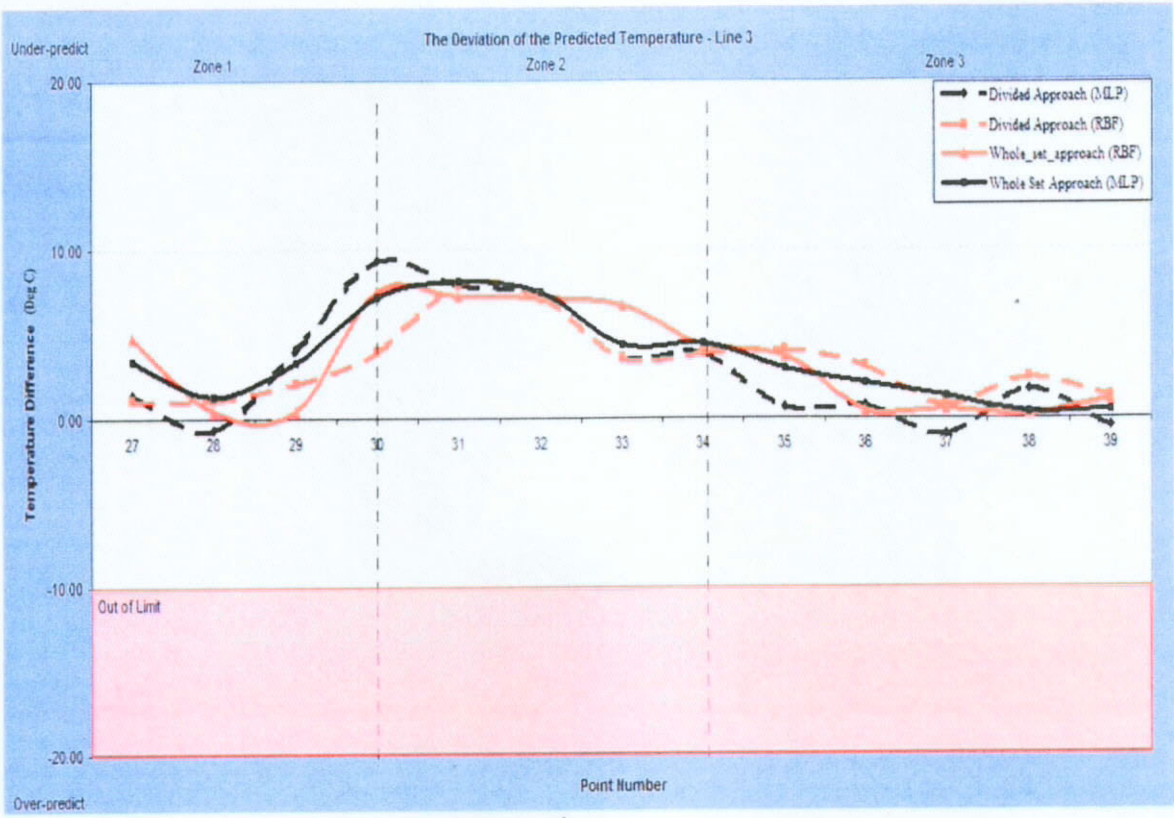


Fig. 73 Deviation of the Predicted Temperature of Line 3 in the First Investigation

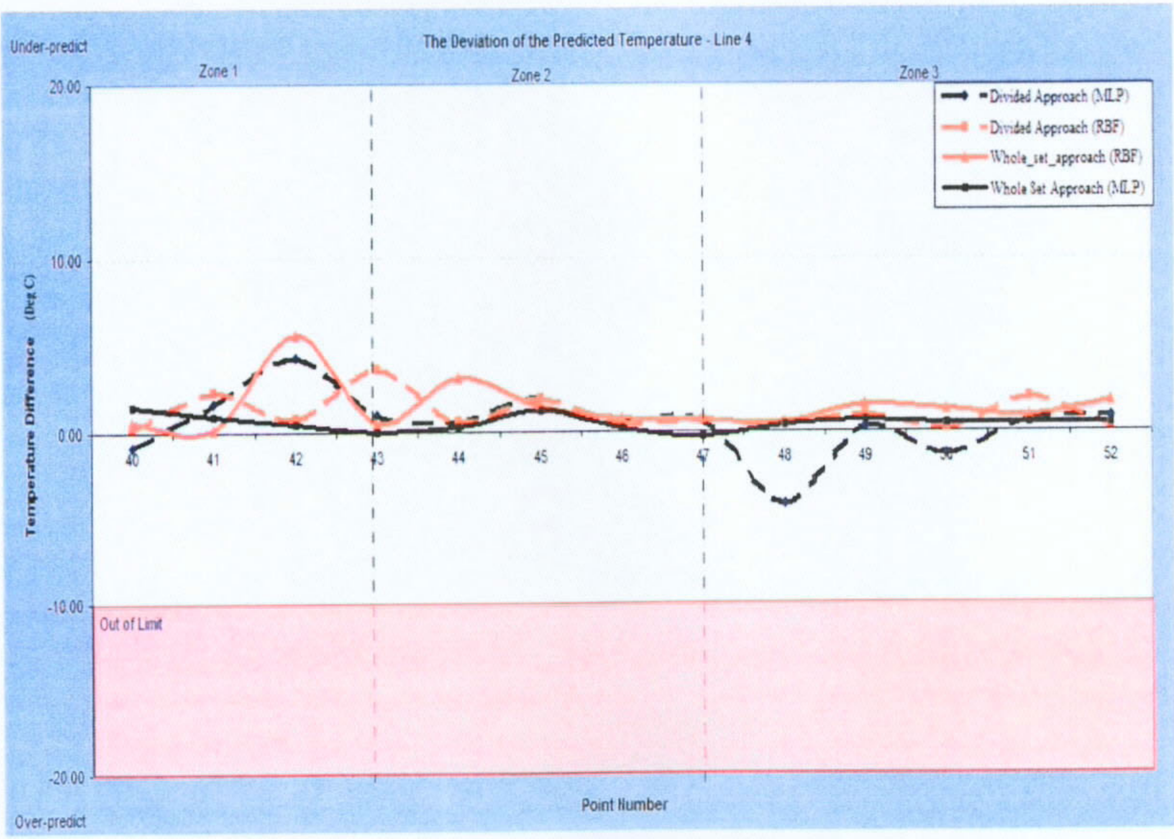


Fig. 74 Deviation of the Predicted Temperature of Line 4 in the First Investigation

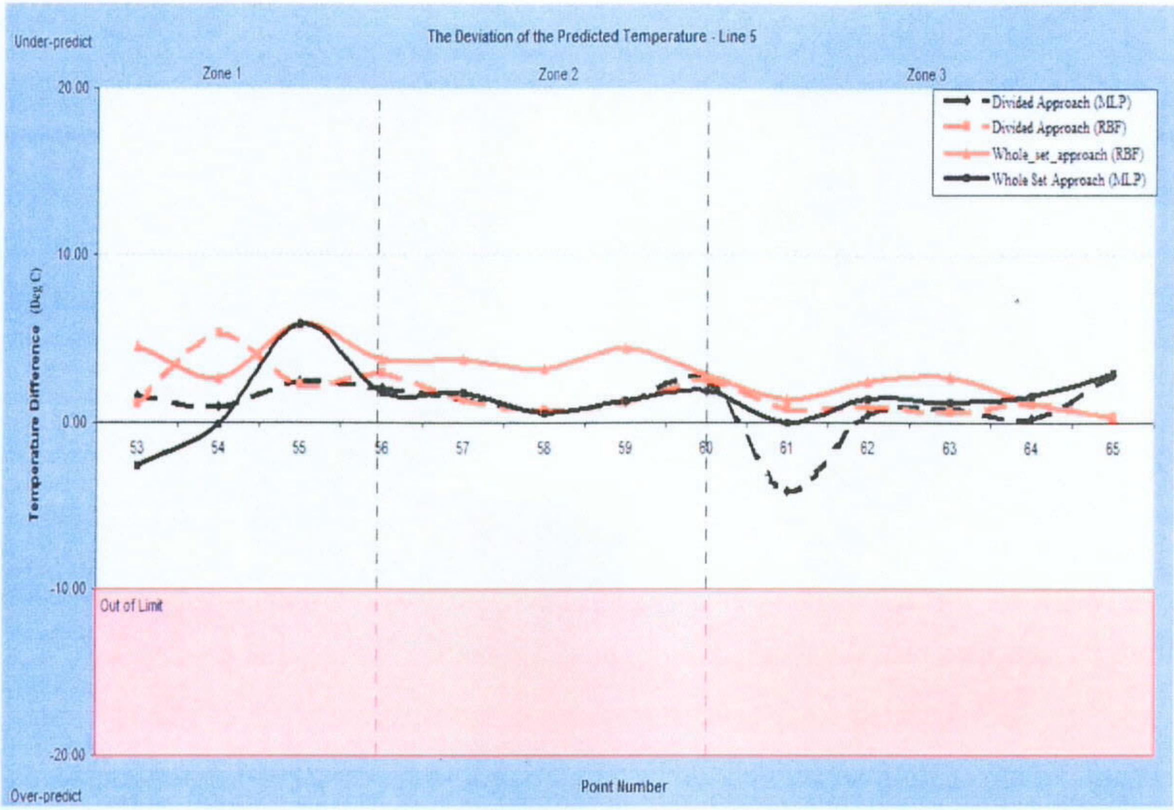


Fig. 75 Deviation of the Predicted Temperature of Line 5 in the First Investigation

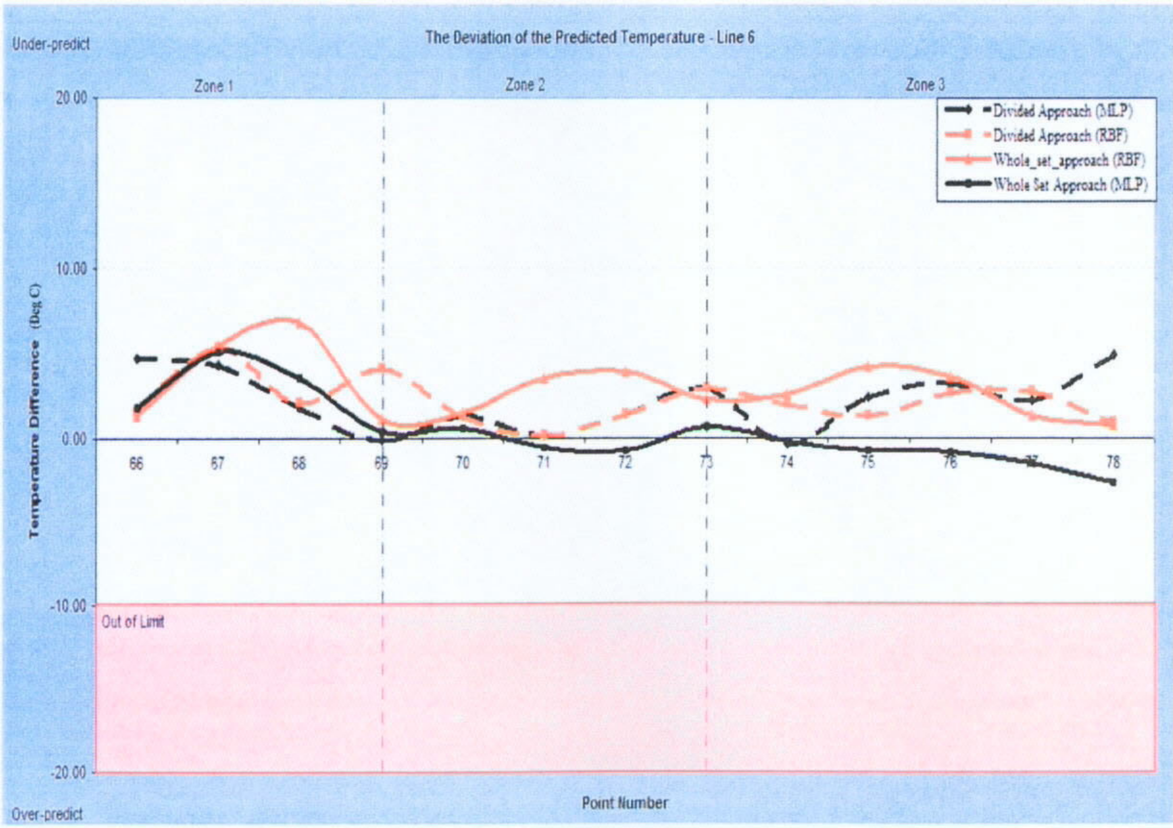


Fig 76 Deviation of the Predicted Temperature of Line 6 in the First Investigation

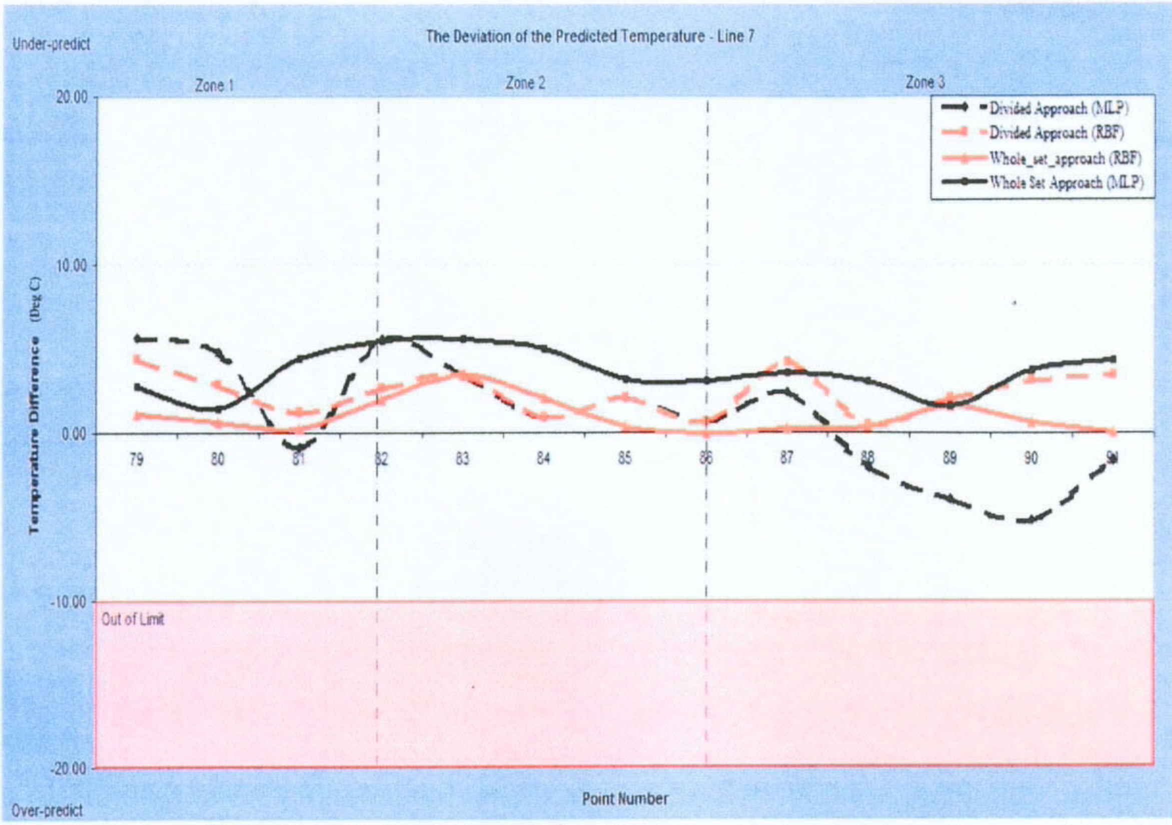


Fig .77 Deviation of the Predicted Temperature of Line 7 in the First Investigation

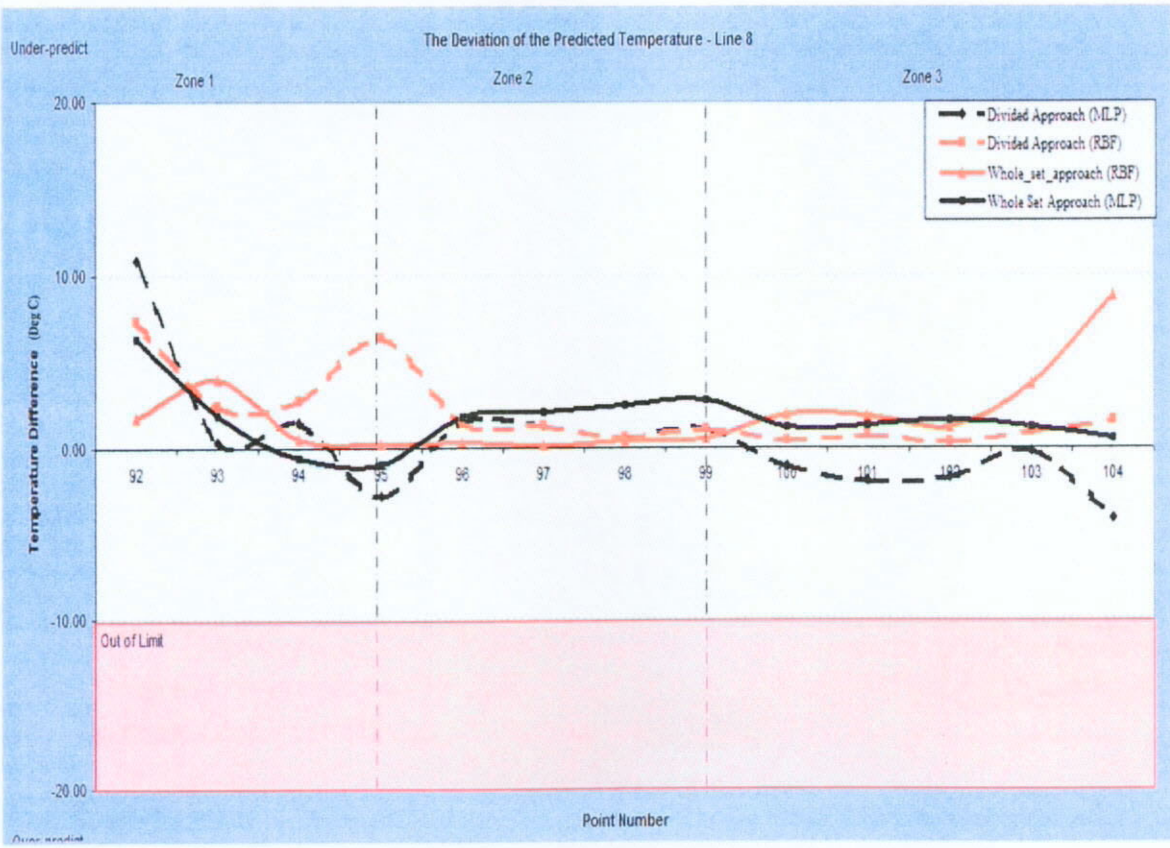


Fig. 78 Deviation of the Predicted Temperature of Line 8 in the First Investigation

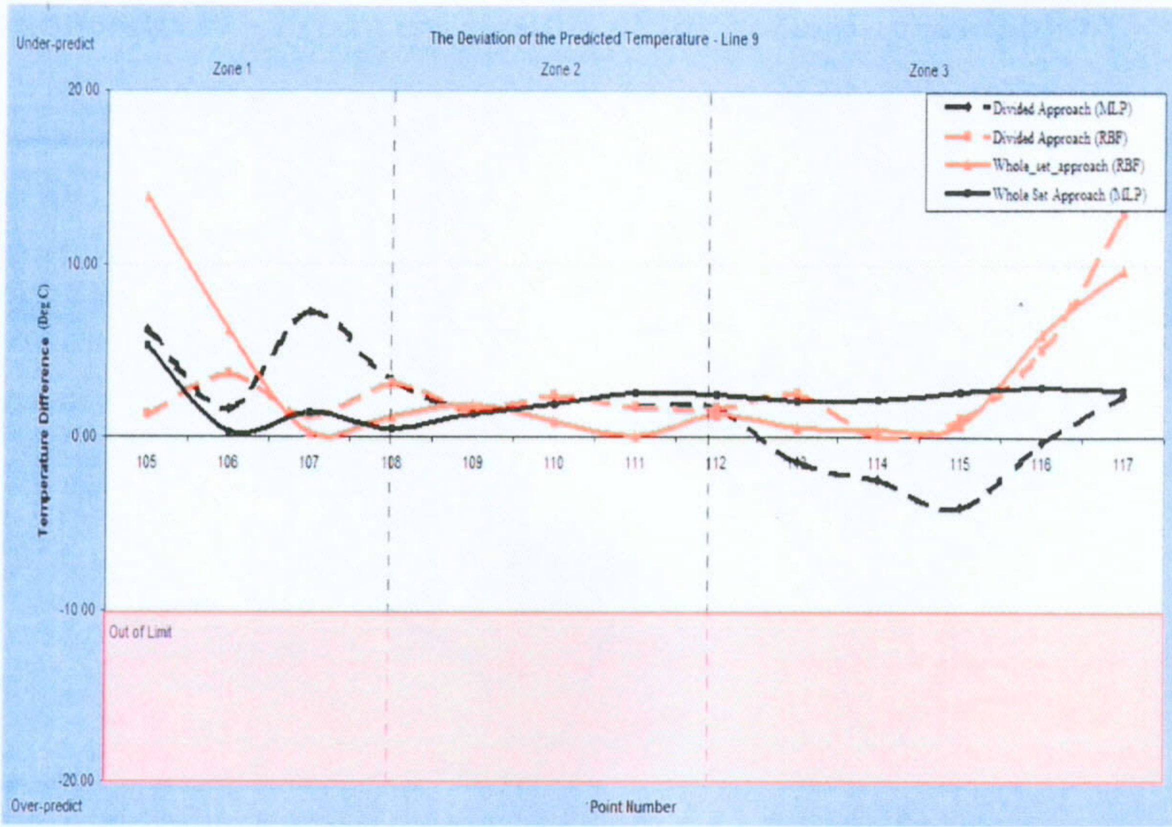


Fig. 79 Deviation of the Predicted Temperature of Line 9 in the First Investigation

Appendix II - Predicted Results of the Second Investigation

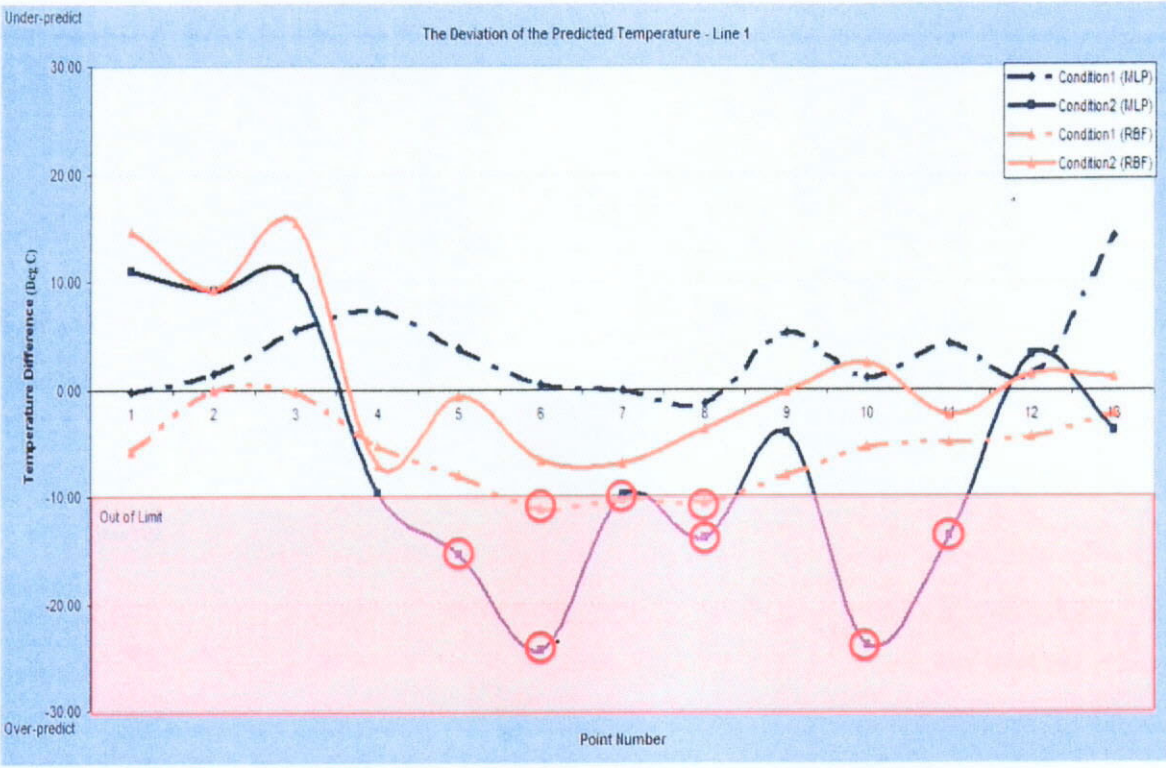


Fig. 80 Deviation of the Predicted Temperature of Line 1 in the Second Investigation

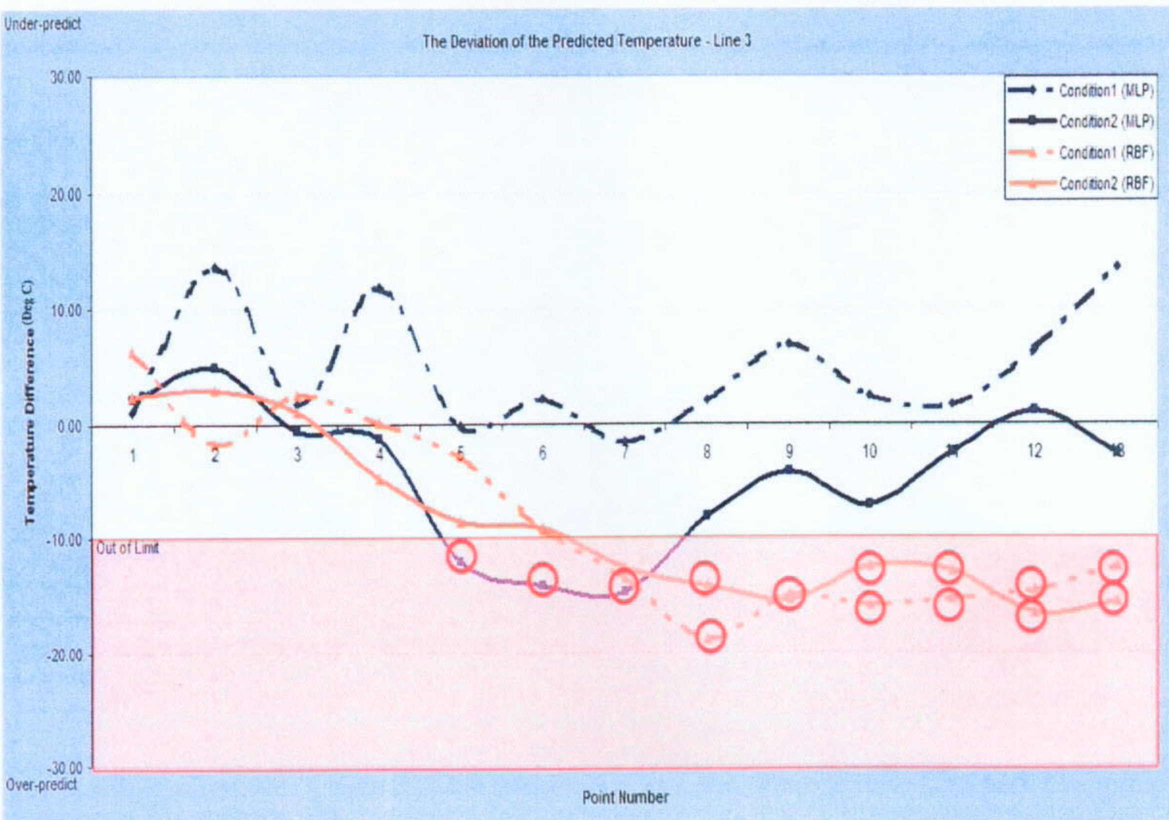


Fig. 81 Deviation of the Predicted Temperature of Line 2 in the Second Investigation

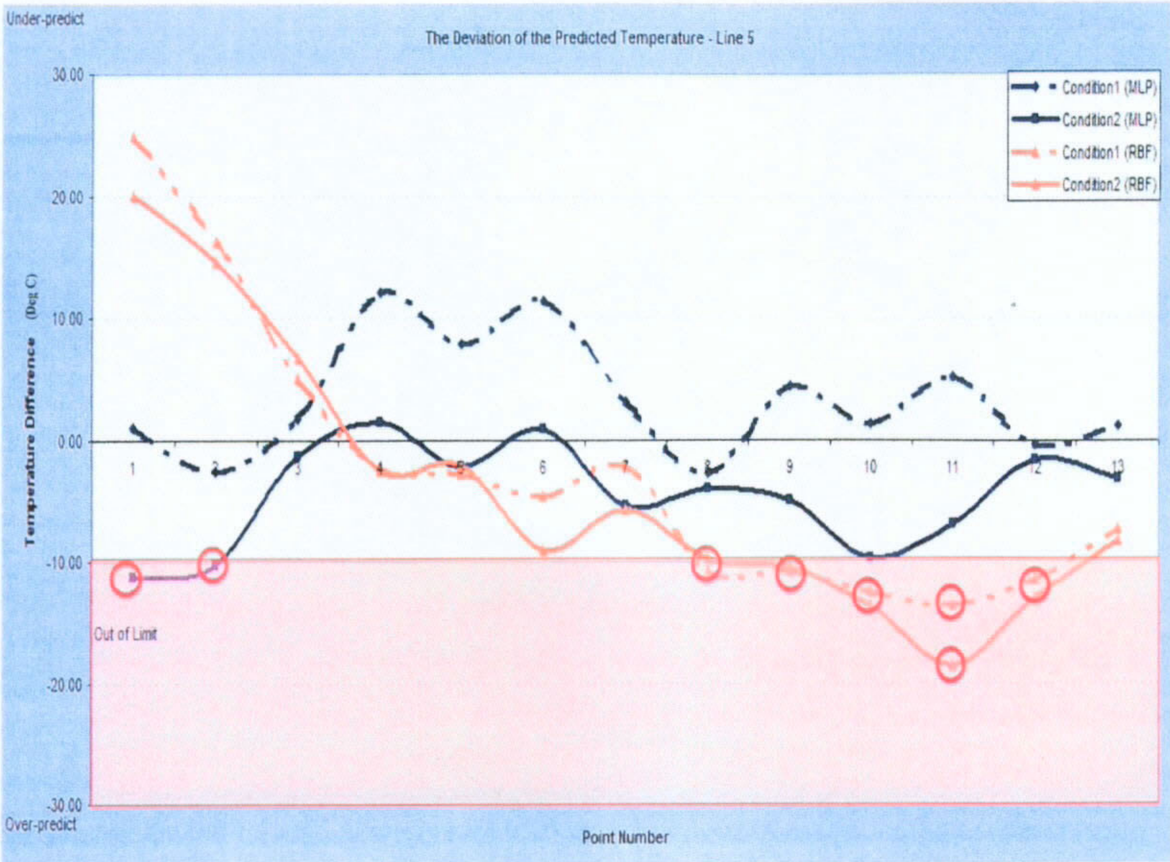


Fig. 82 Deviation of the Predicted Temperature of Line 3 in the Second Investigation

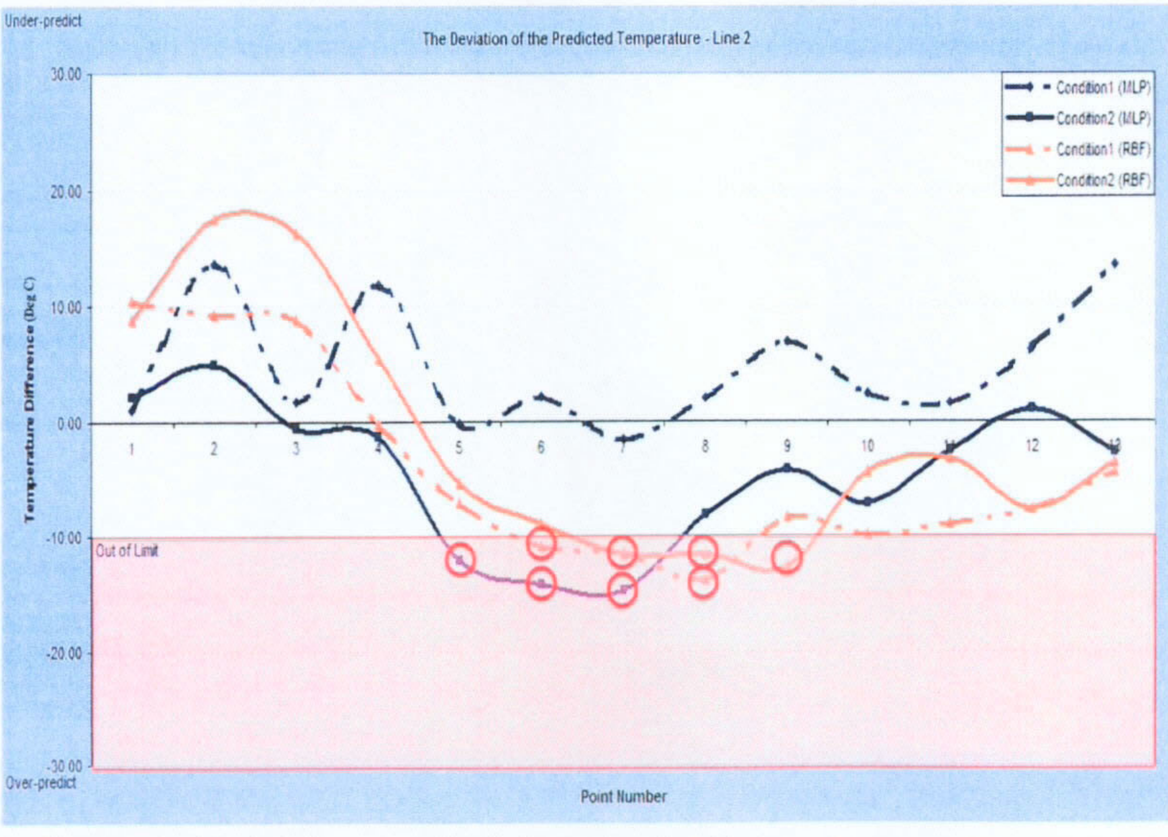


Fig. 83 Deviation of the Predicted Temperature of Line 4 in the Second Investigation

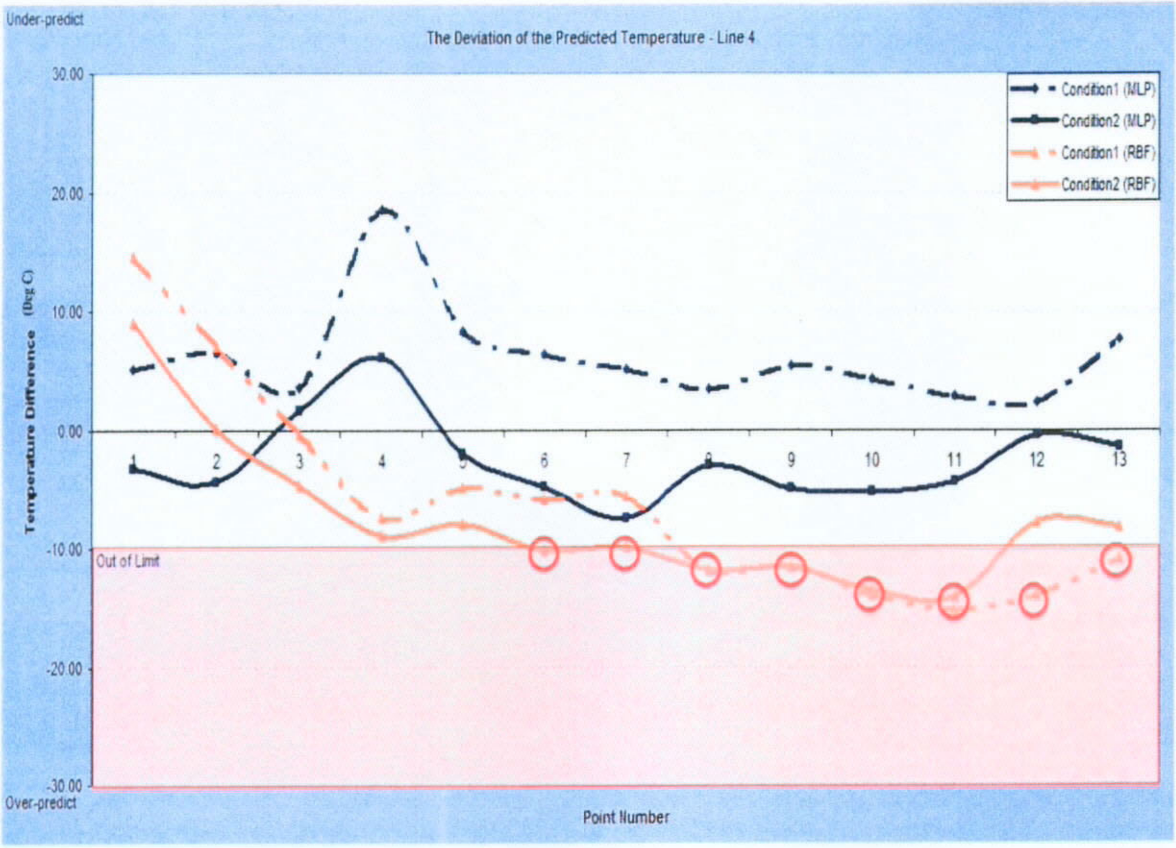


Fig. 84 Deviation of the Predicted Temperature of Line 5 in the Second Investigation

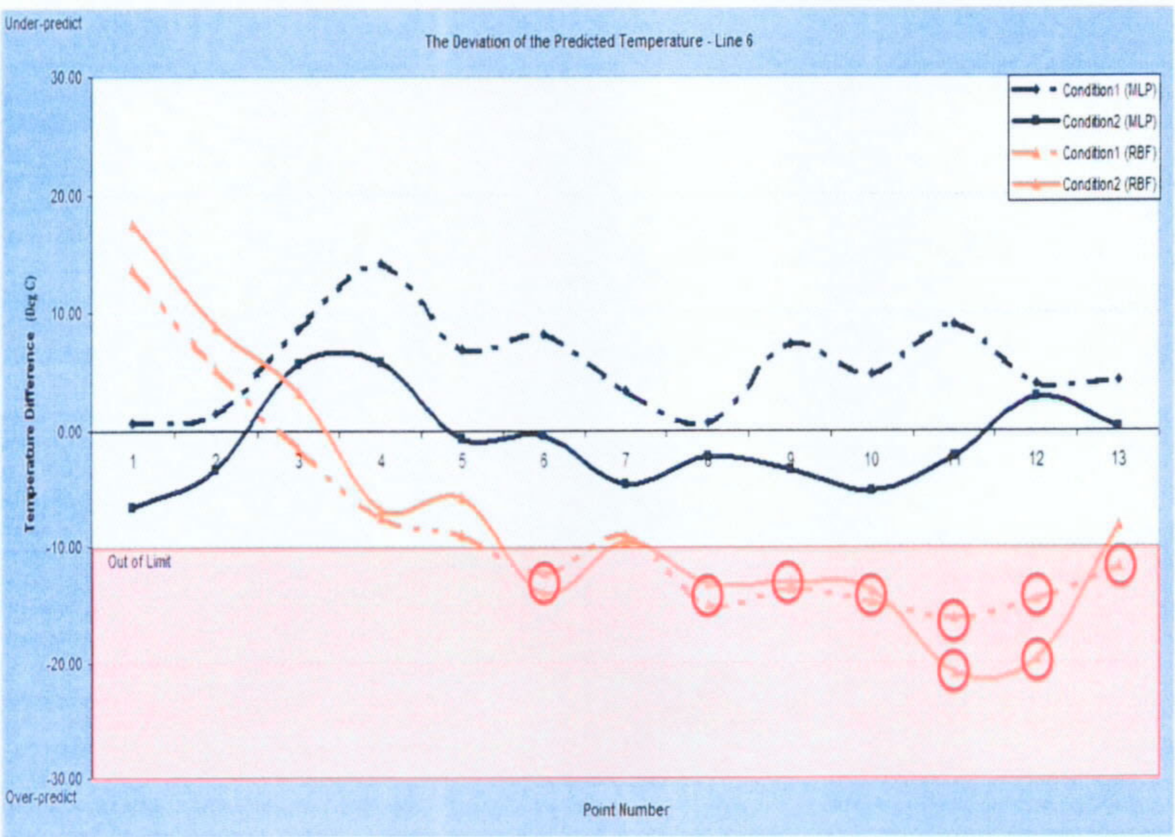


Fig. 85 Deviation of the Predicted Temperature of Line 6 in the Second Investigation

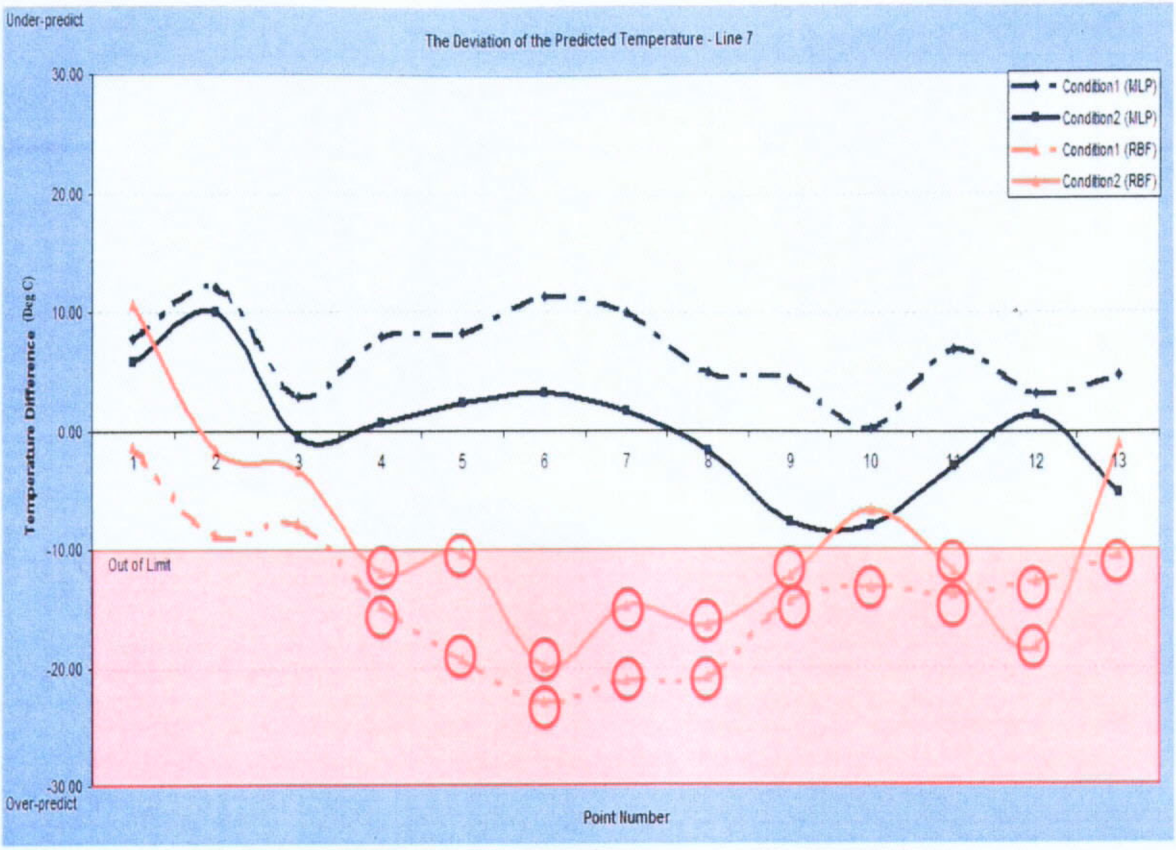


Fig. 86 Deviation of the Predicted Temperature of Line 7 in the Second Investigation

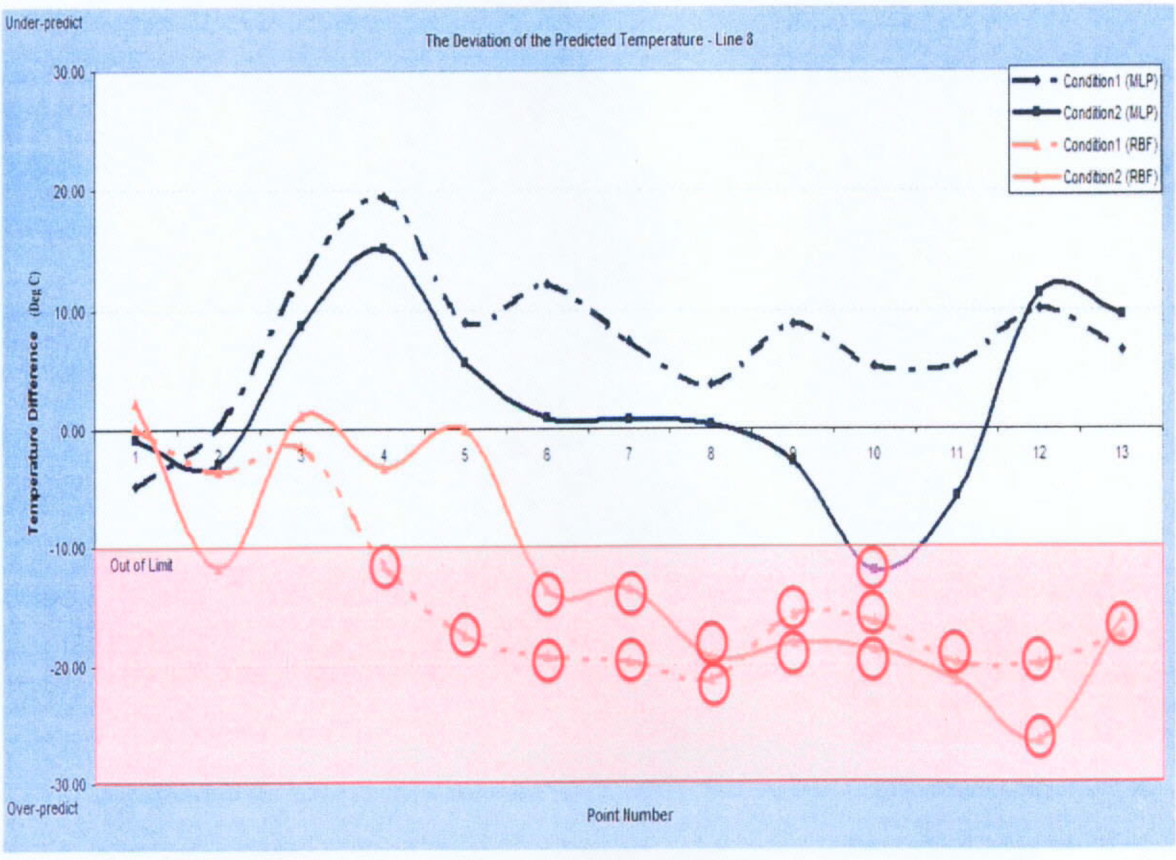


Fig. 87 Deviation of the Predicted Temperature of Line 8 in the Second Investigation

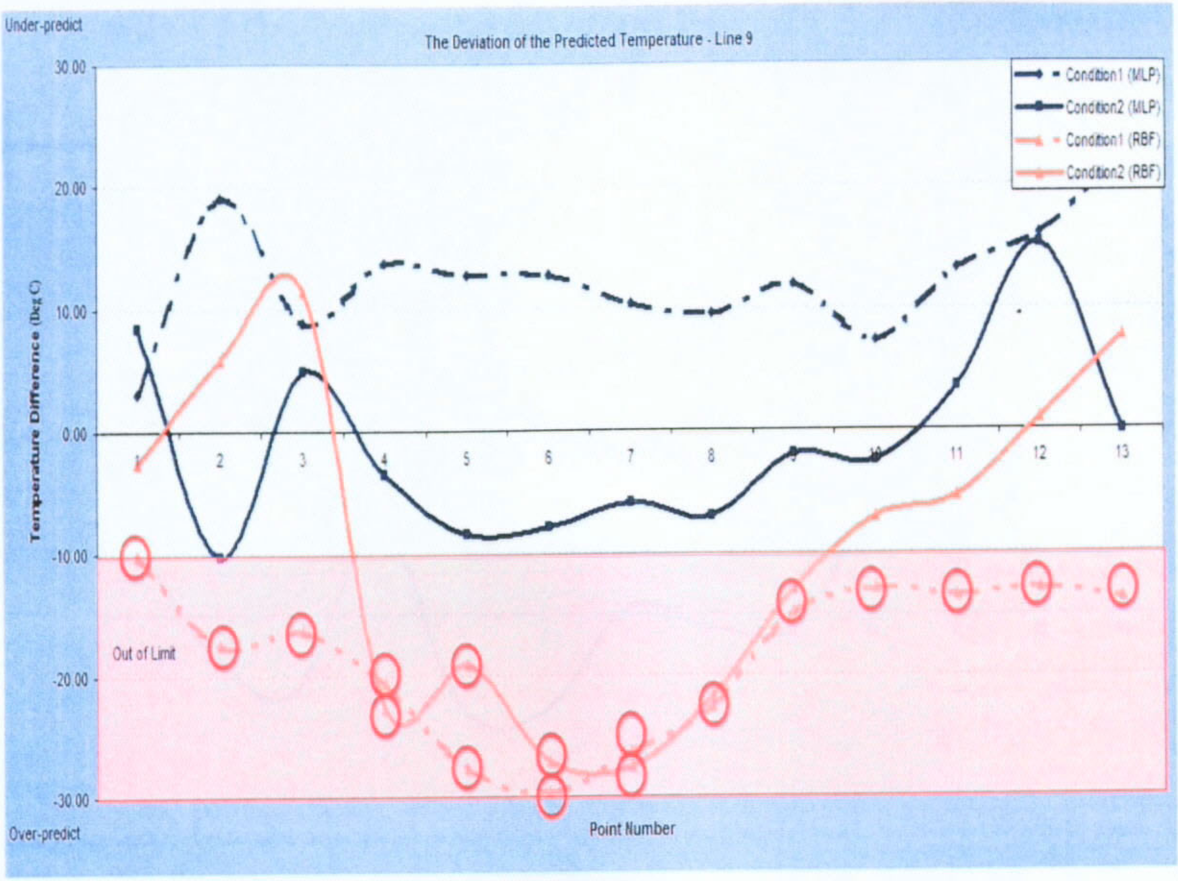


Fig. 88 Deviation of the Predicted Temperature of Line 9 in the Second Investigation

Appendix III - Predicted Results of the Confirmation Investigation

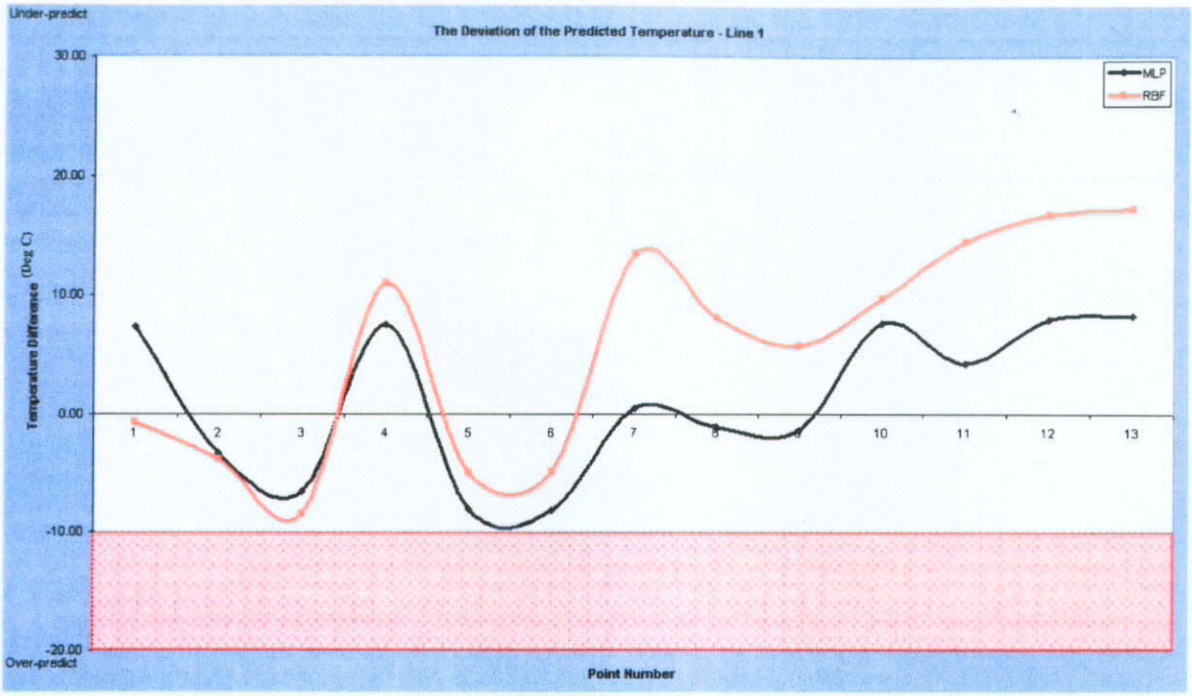


Fig. 89 Deviation of the Predicted Temperature of Line 1 in the Confirmation Investigation

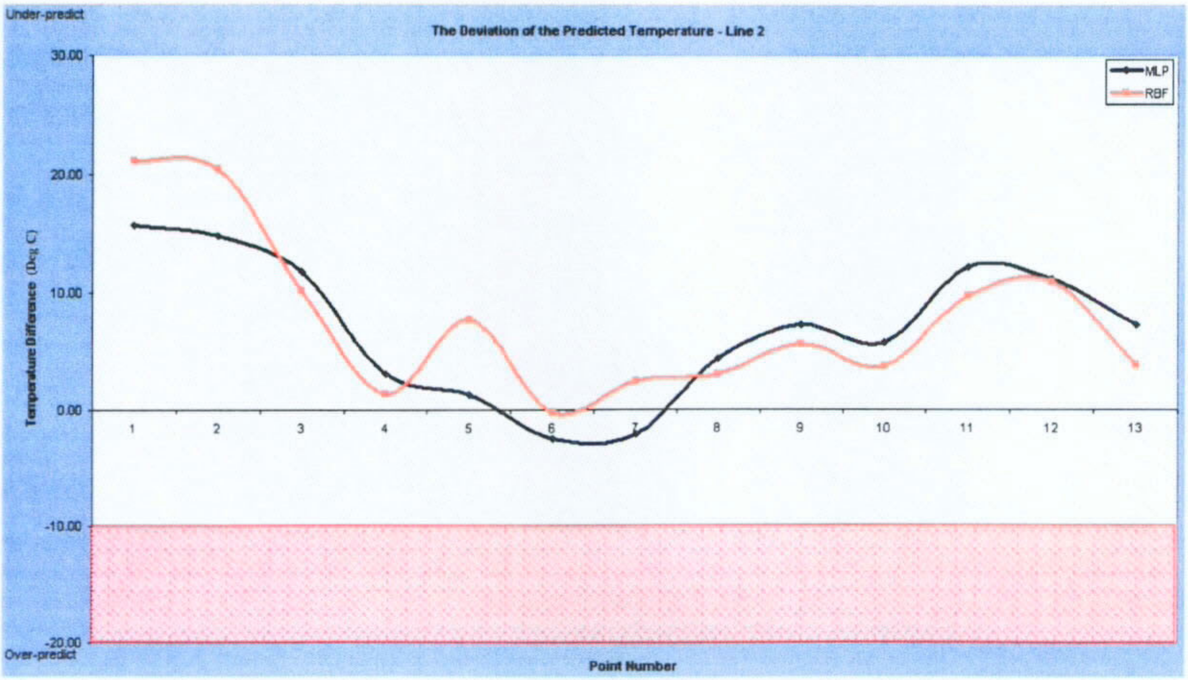


Fig. 90 Deviation of the Predicted Temperature of Line 2 in the Confirmation Investigation

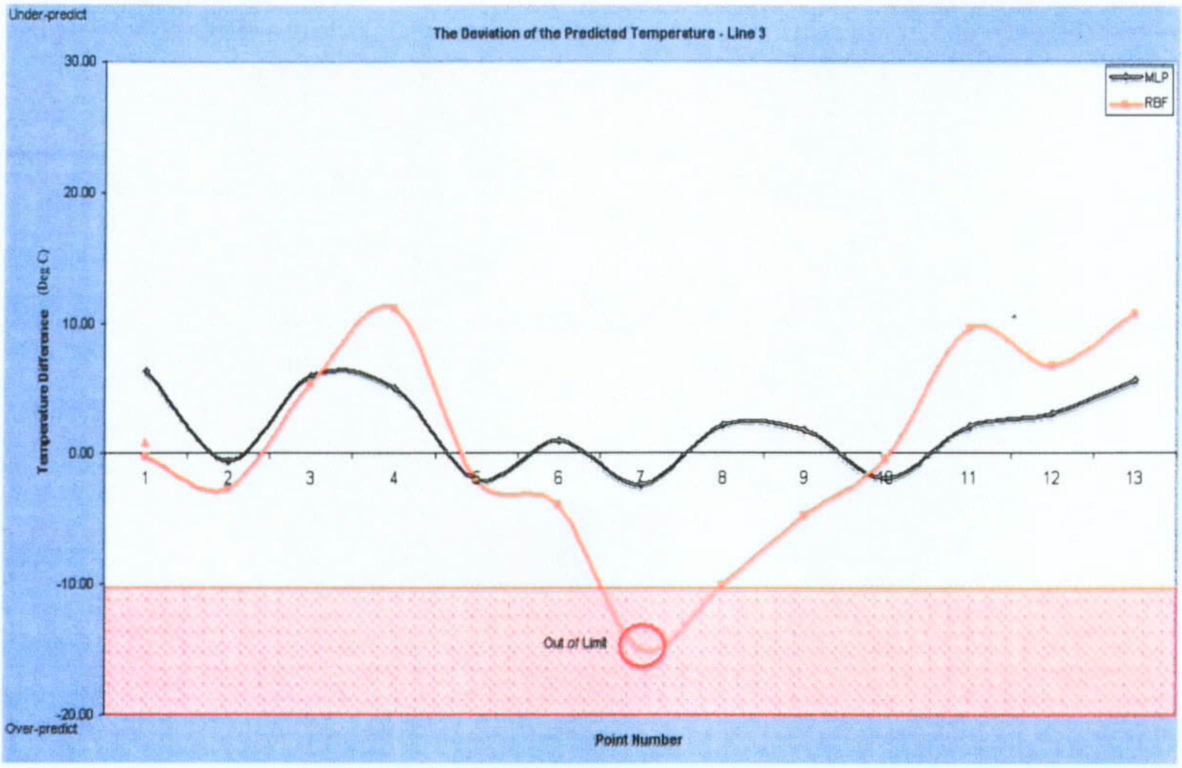


Fig. 91 Deviation of the Predicted Temperature of Line 3 in the Confirmation Investigation

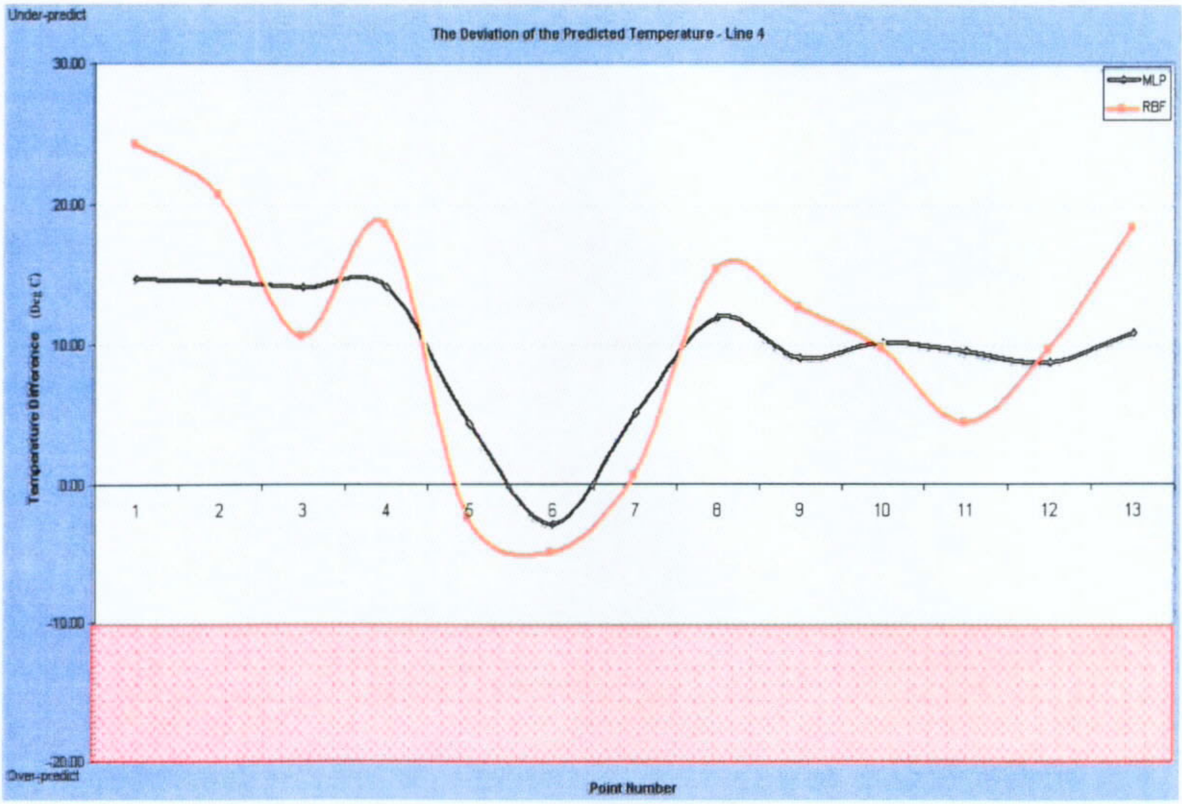


Fig. 92 Deviation of the Predicted Temperature of Line 4 in the Confirmation Investigation

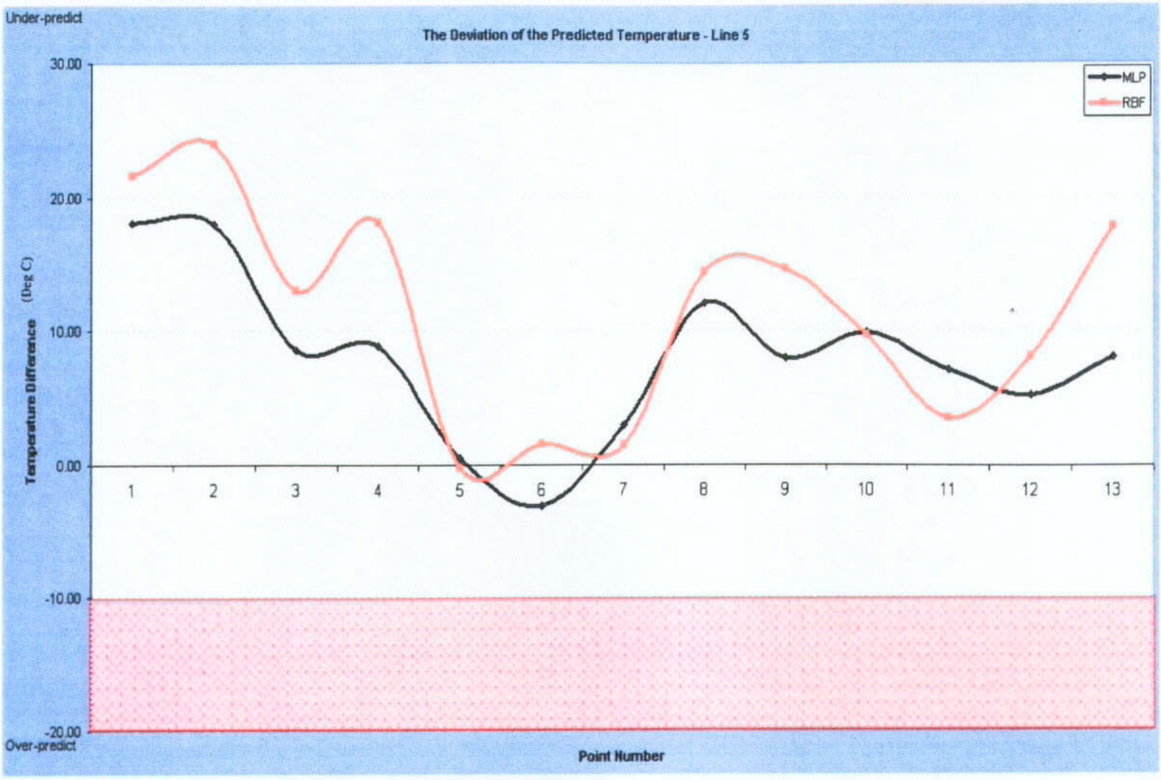


Fig. 93 Deviation of the Predicted Temperature of Line 5 in the Confirmation Investigation

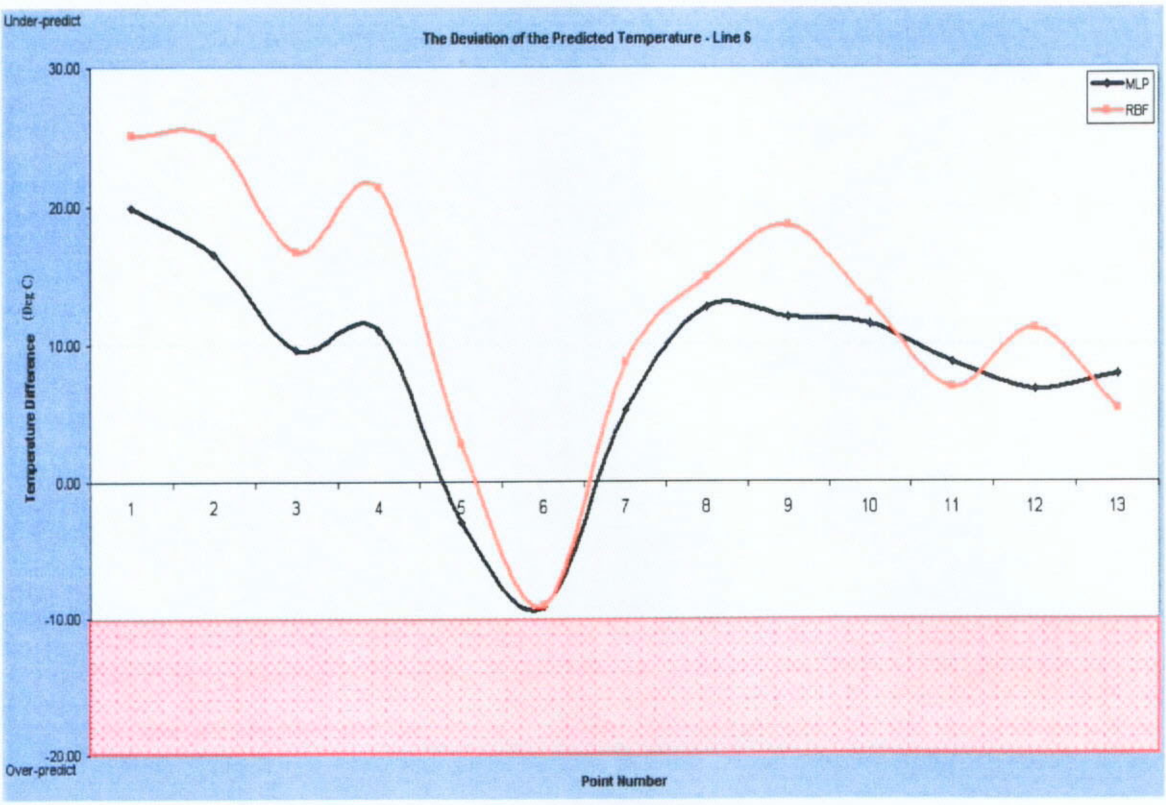


Fig. 94 Deviation of the Predicted Temperature of Line 6 in the Confirmation Investigation

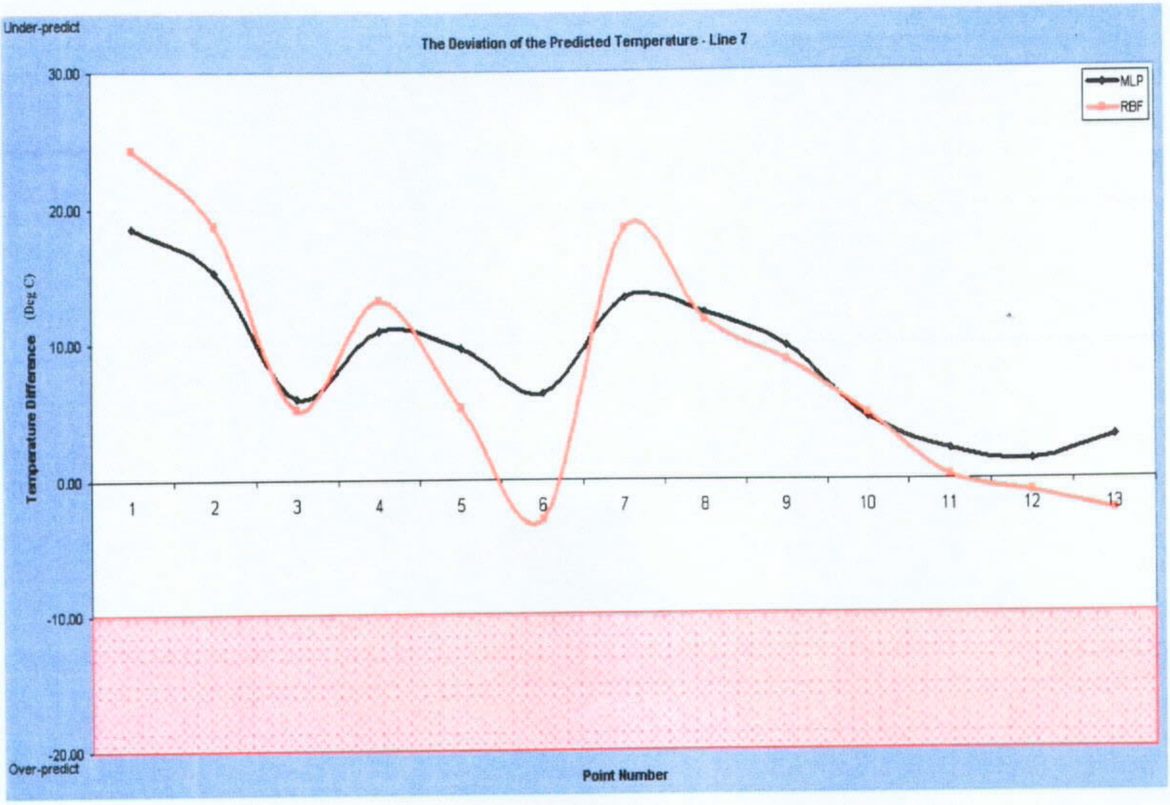


Fig. 95 Deviation of the Predicted Temperature of Line 7 in the Confirmation Investigation

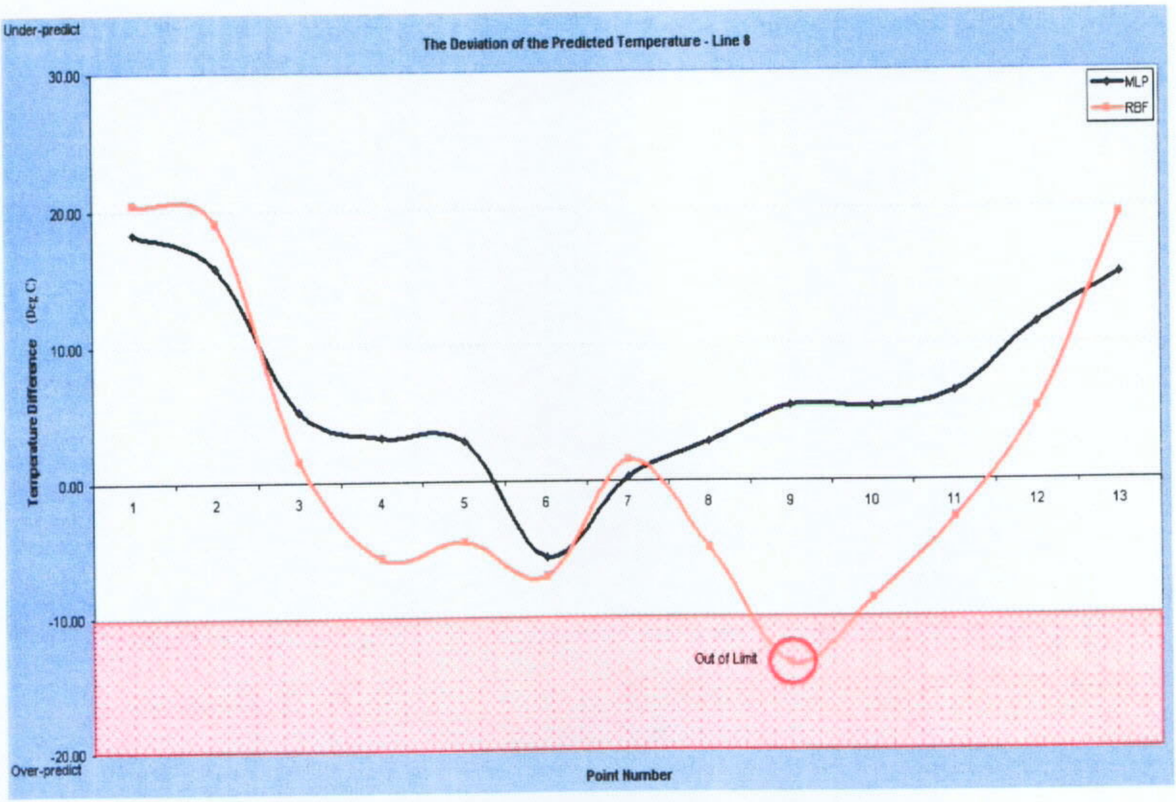


Fig. 96 Deviation of the Predicted Temperature of Line 8 in the Confirmation Investigation

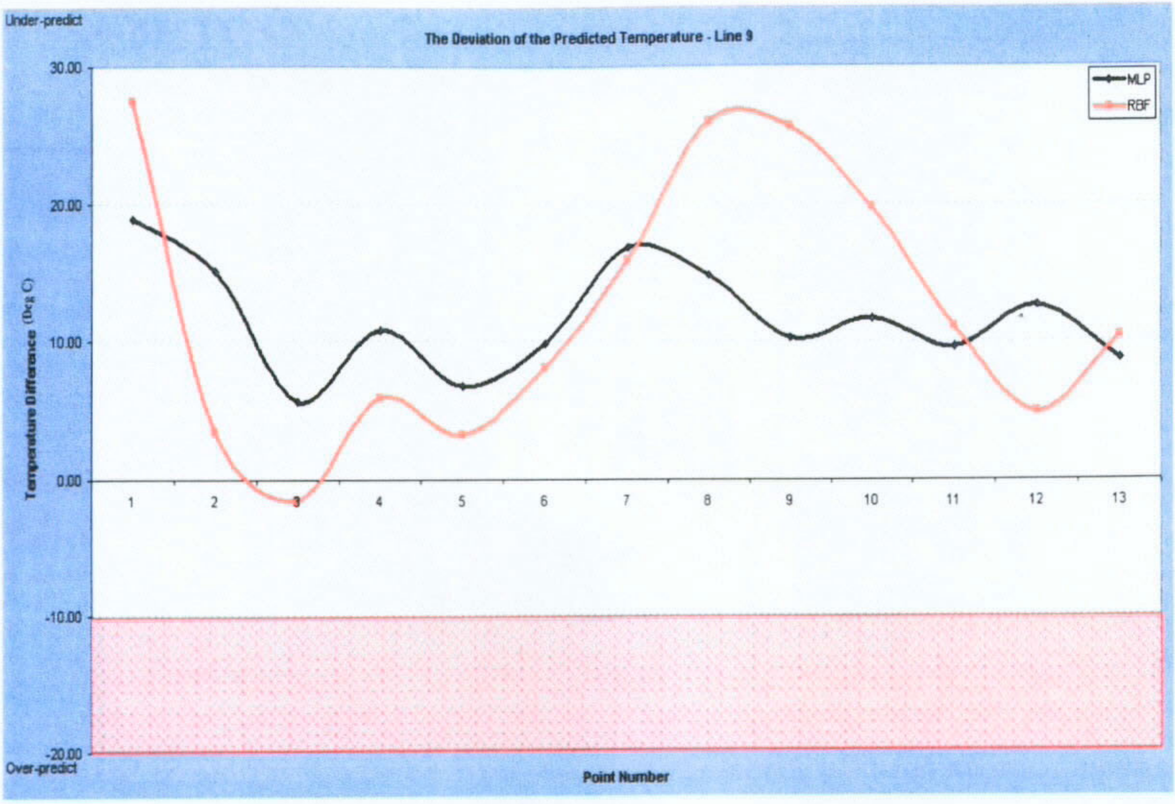


Fig. 97 Deviation of the Predicted Temperature of Line 9 in the Confirmation Investigation

Appendix IV - Experiment Result of the Different Toaster

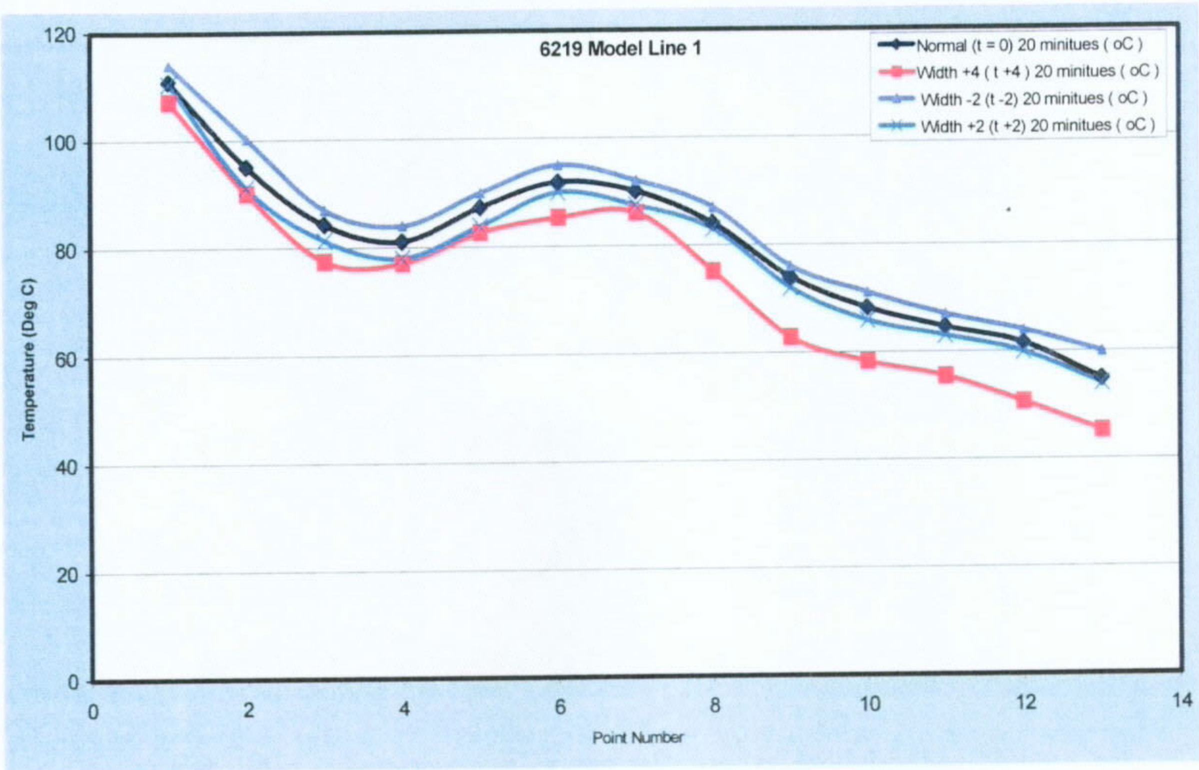


Fig. 98 Experimental Temperature Results of Model 1 (Line 1)

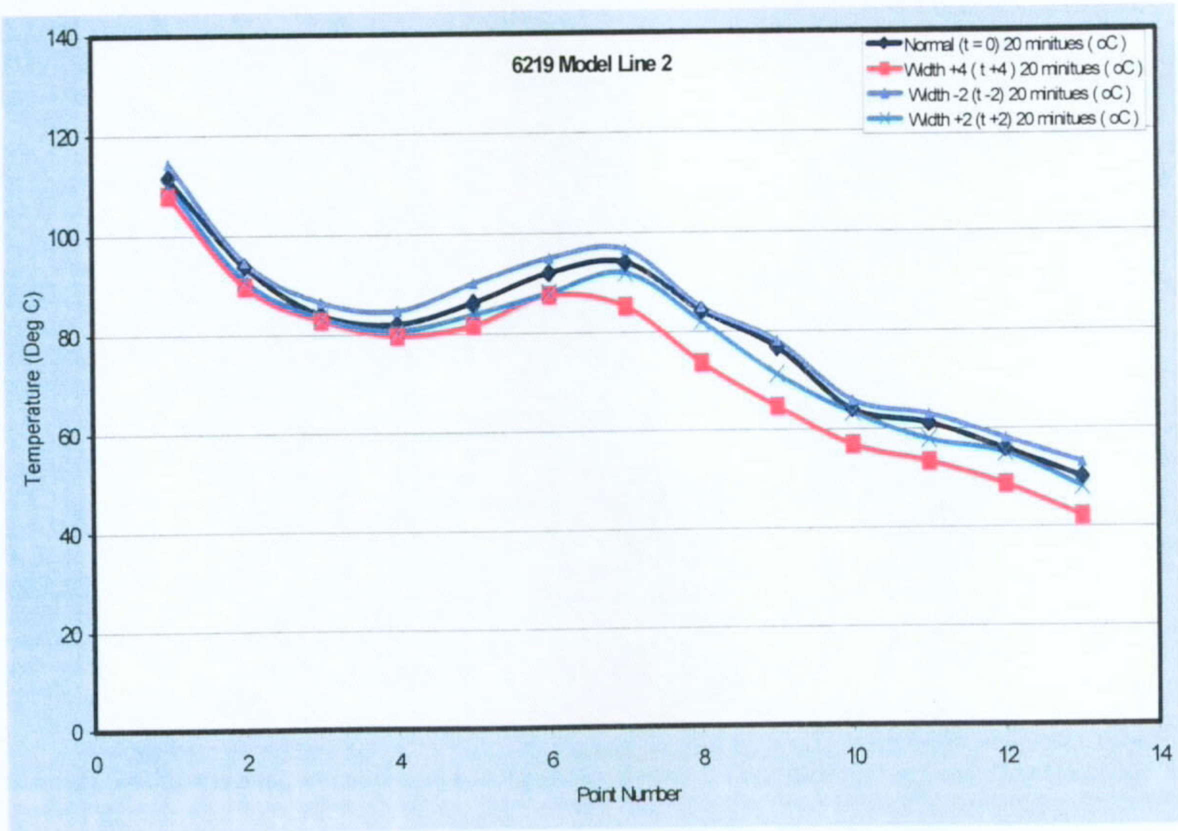


Fig. 99 Experimental Temperature Results of Model 1 (Line 2)

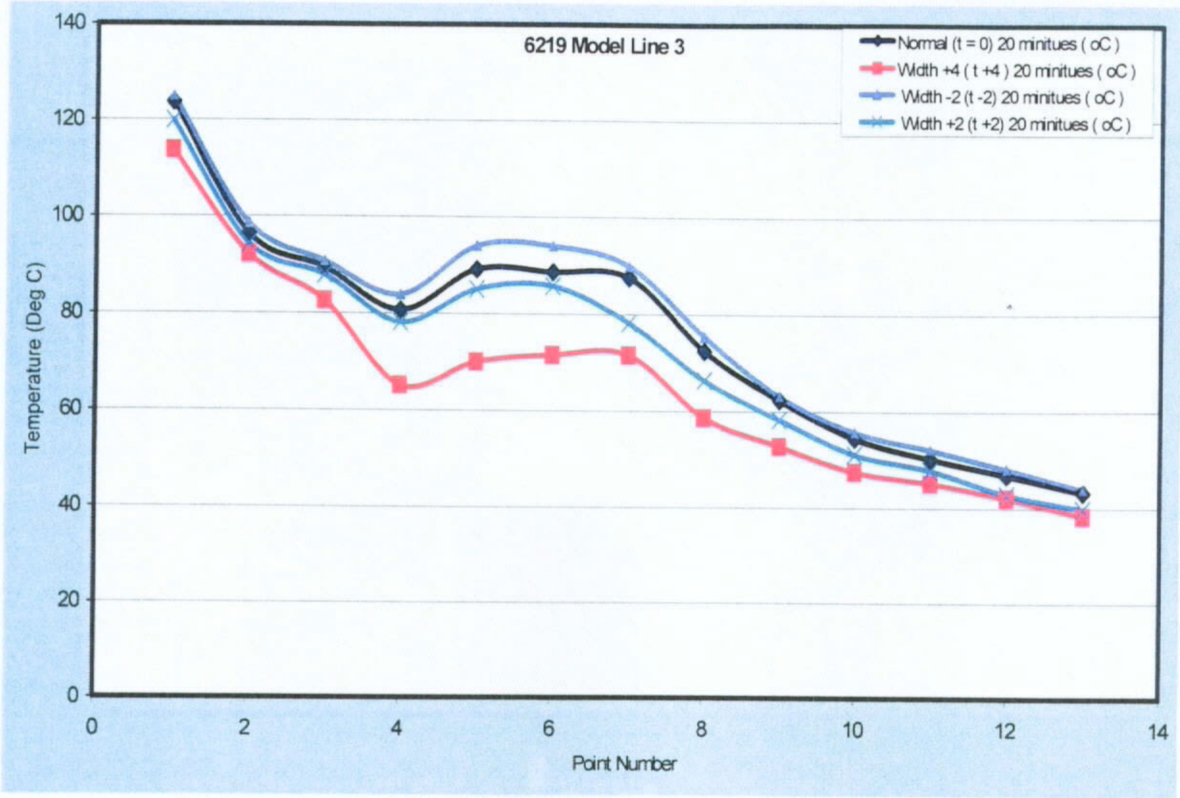


Fig. 100 Experimental Temperature Results of Model 1 (Line 3)

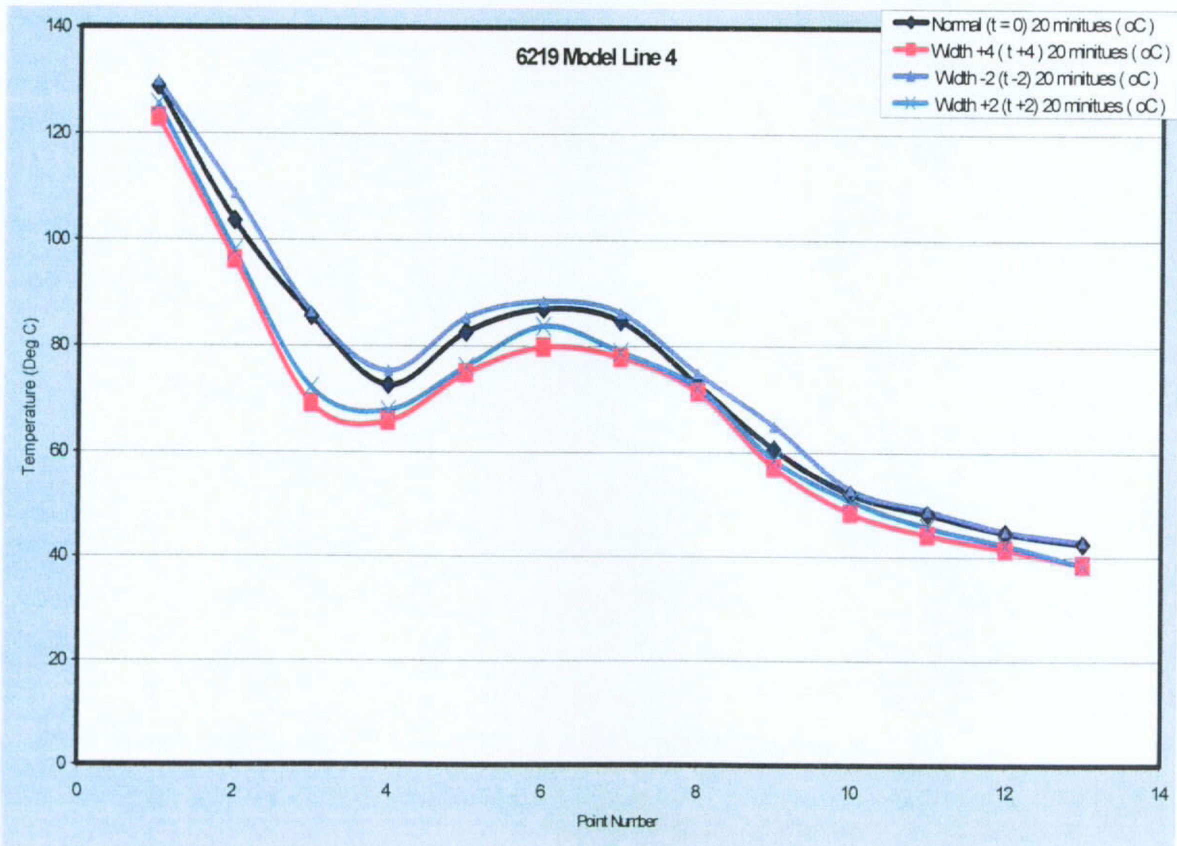


Fig. 101 Experimental Temperature Results of Model 1 (Line 4)

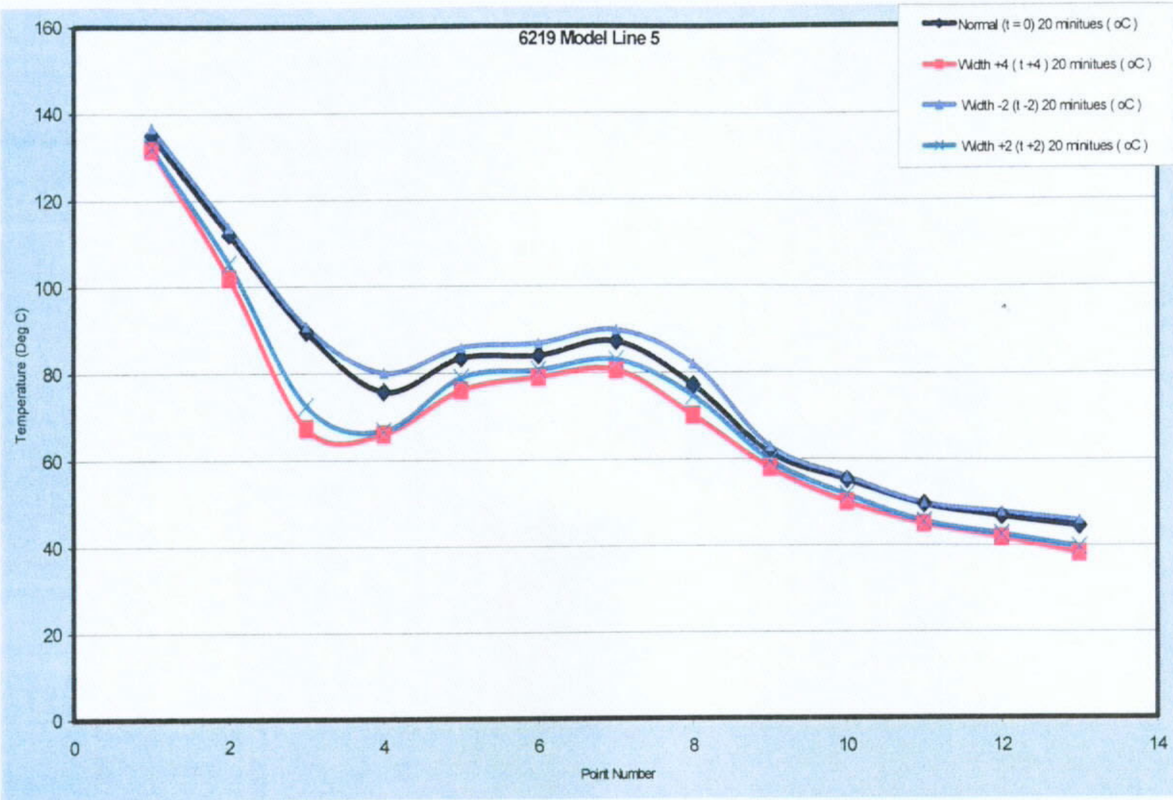


Fig. 102 Experimental Temperature Results of Model 1 (Line 5)

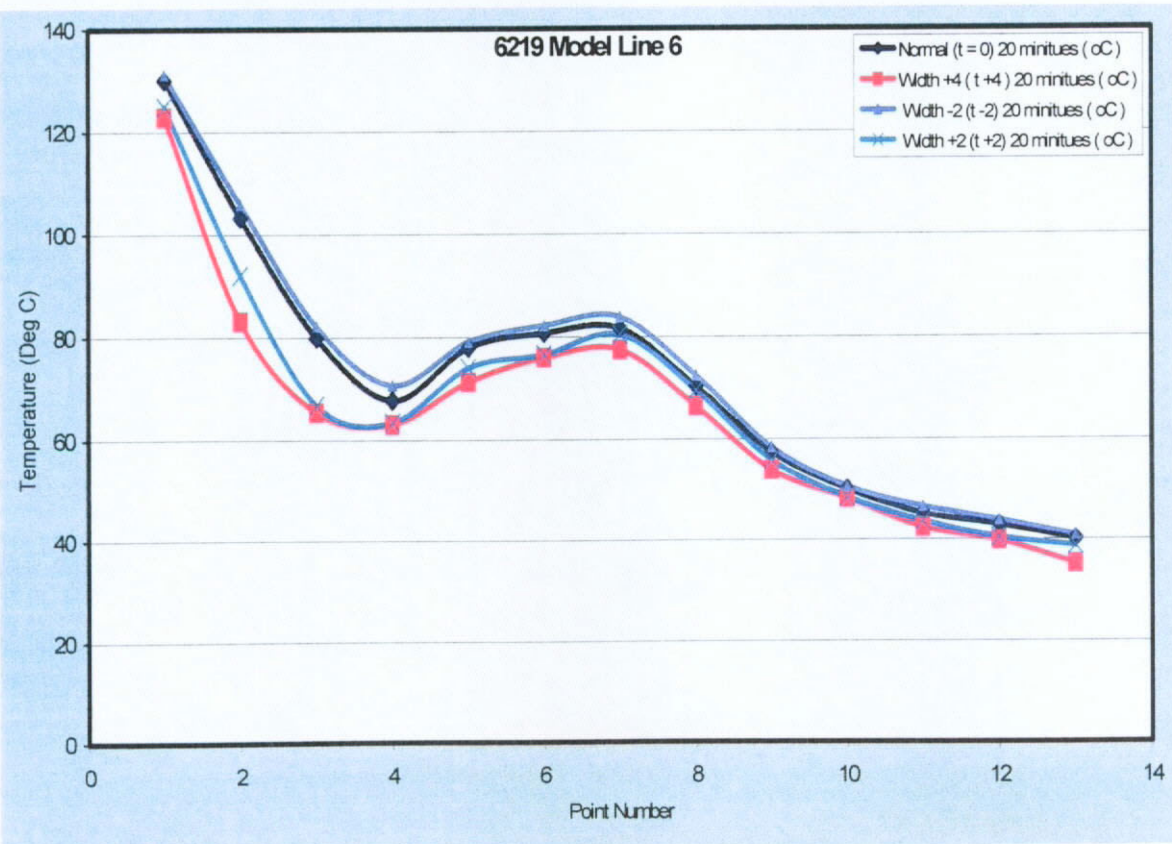


Fig. 103 Experimental Temperature Results of Model 1 (Line 6)

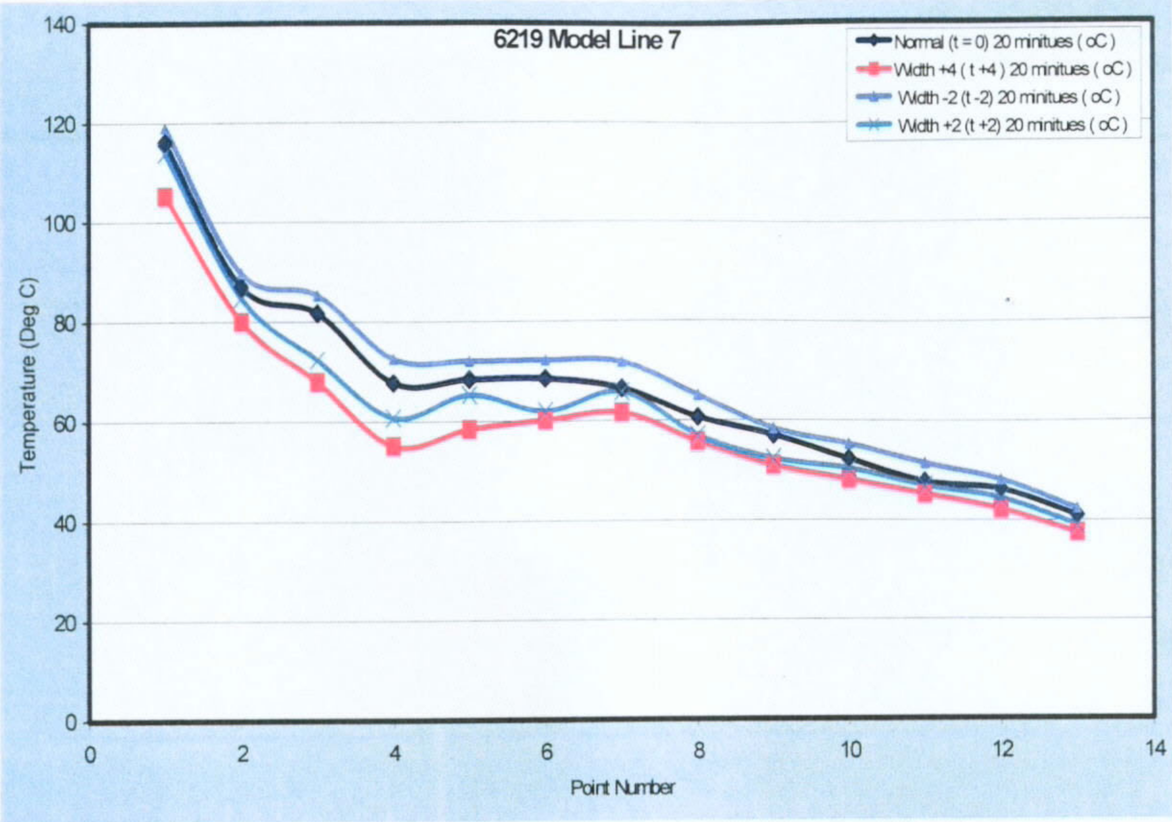


Fig. 104 Experimental Temperature Results of Model 1 (Line 7)

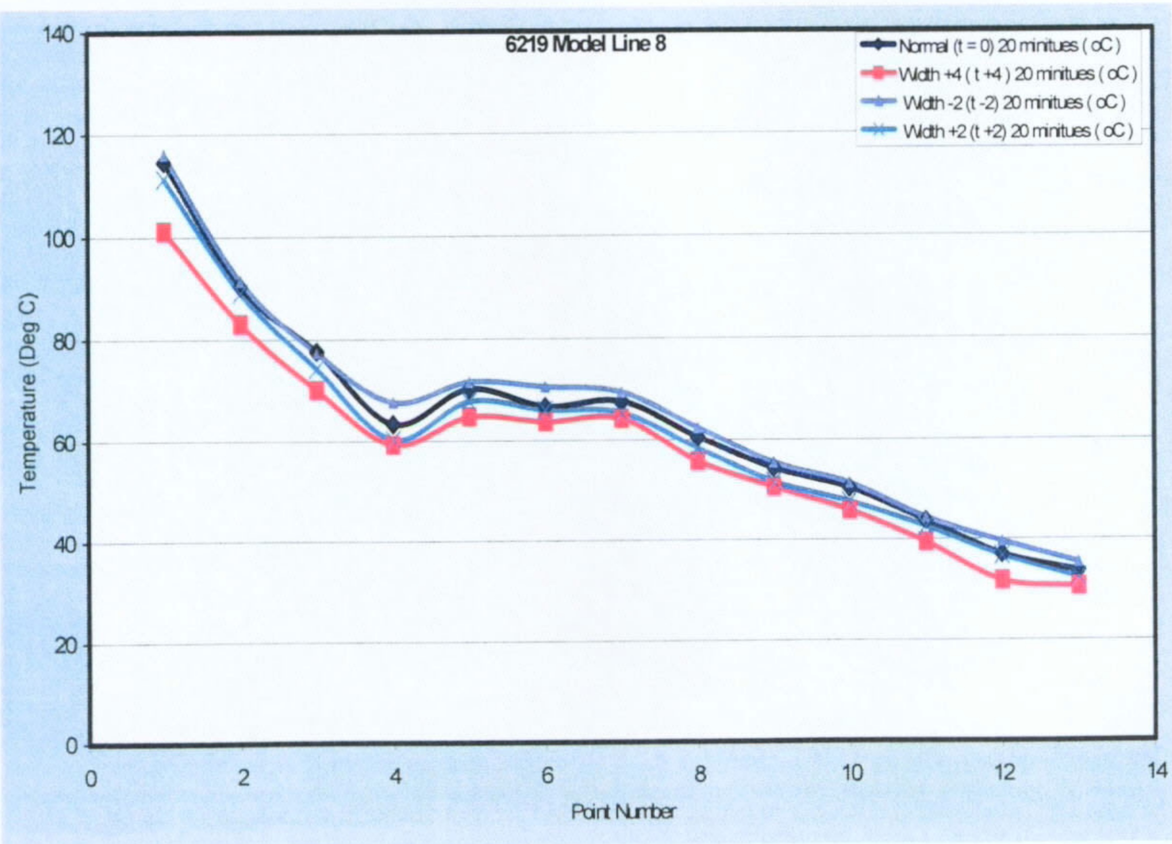


Fig. 105 Experimental Temperature Results of Model 1 (Line 8)

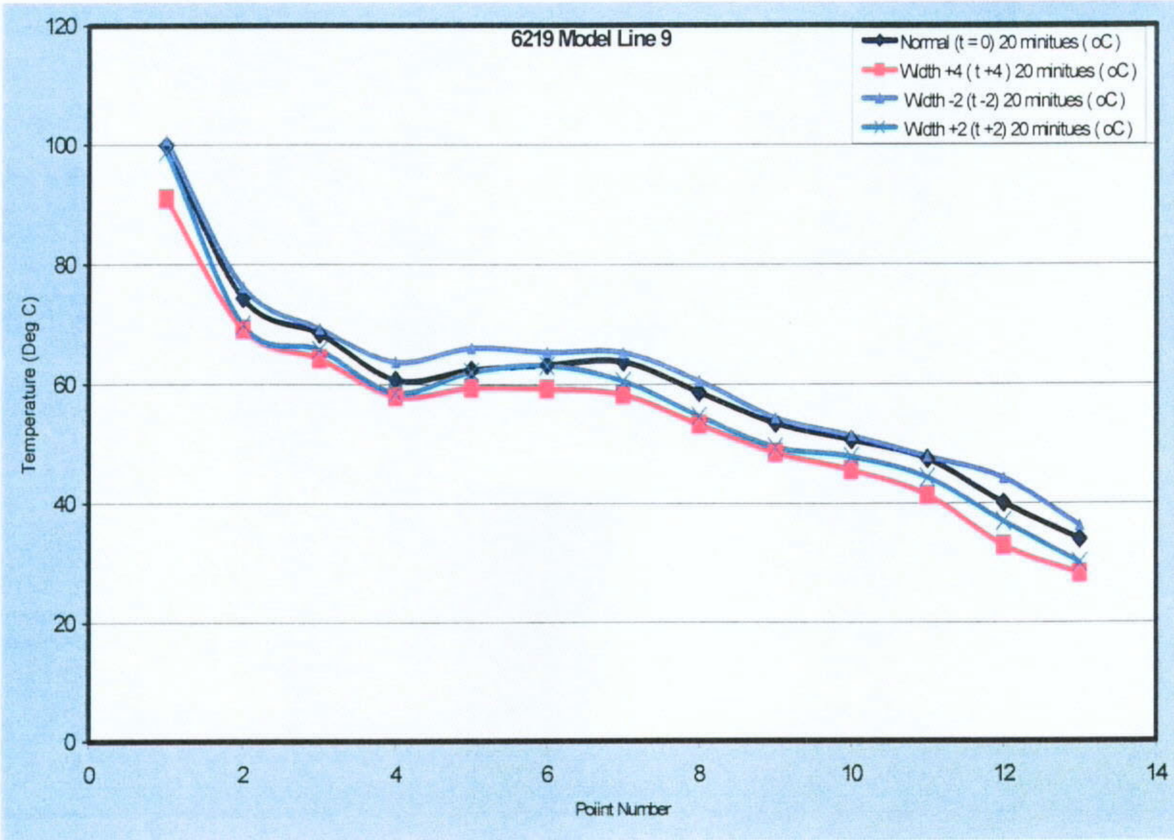


Fig. 106 Experimental Temperature Results of Model 1 (Line 9)

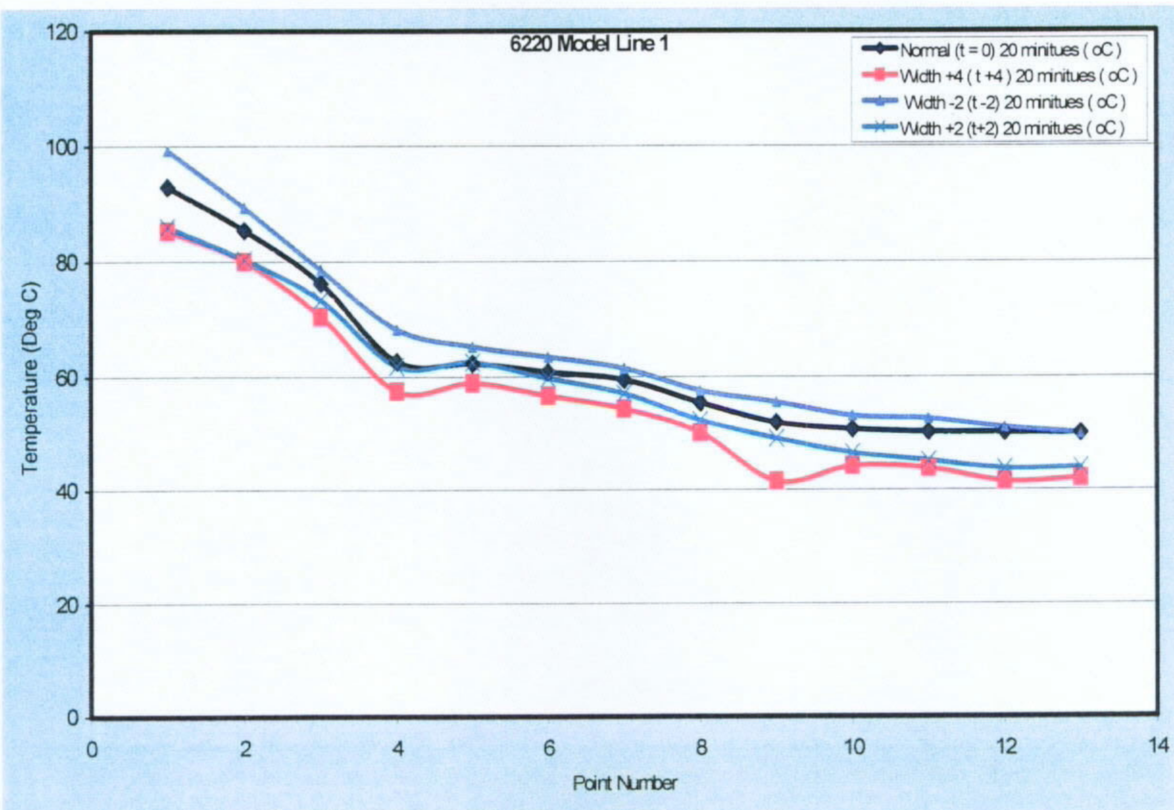


Fig. 107 Experimental Temperature Results of Model 2 (Line 1)

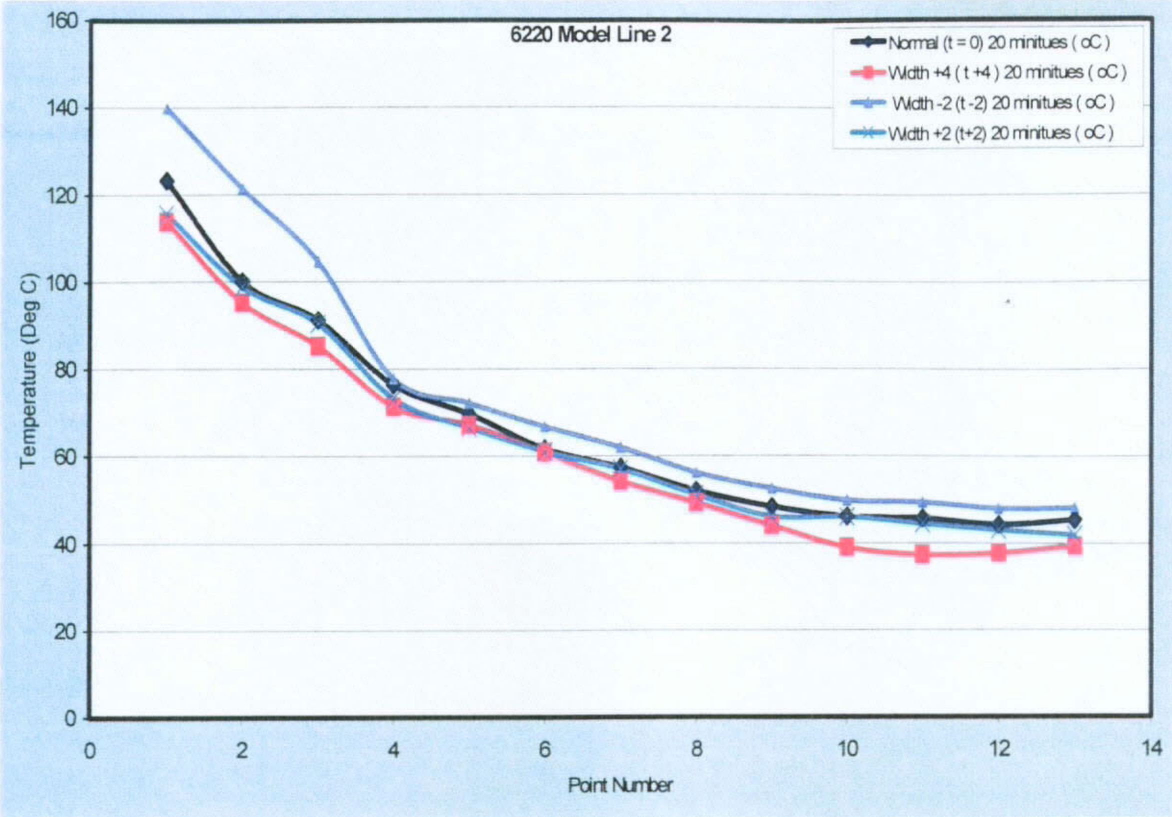


Fig. 108 Experimental Temperature Results of Model 2 (Line 2)

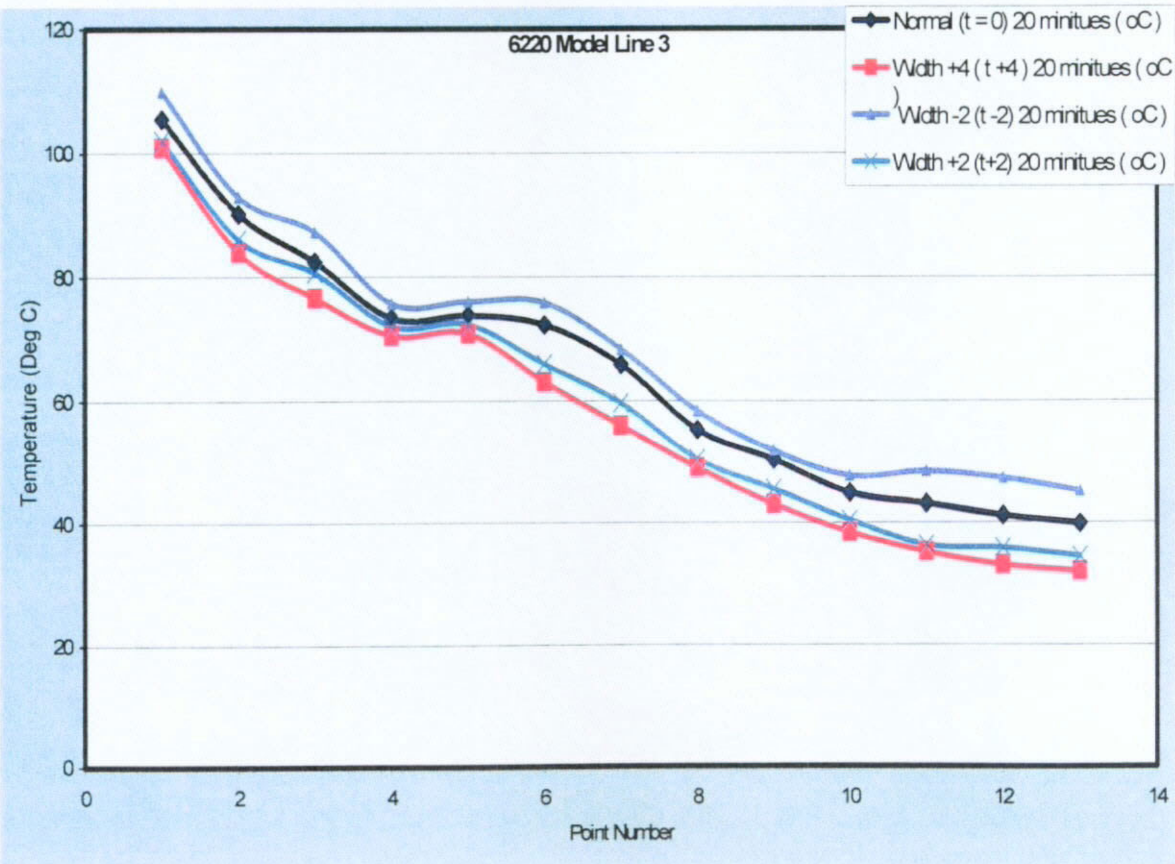


Fig. 109 Experimental Temperature Results of Model 2 (Line 3)

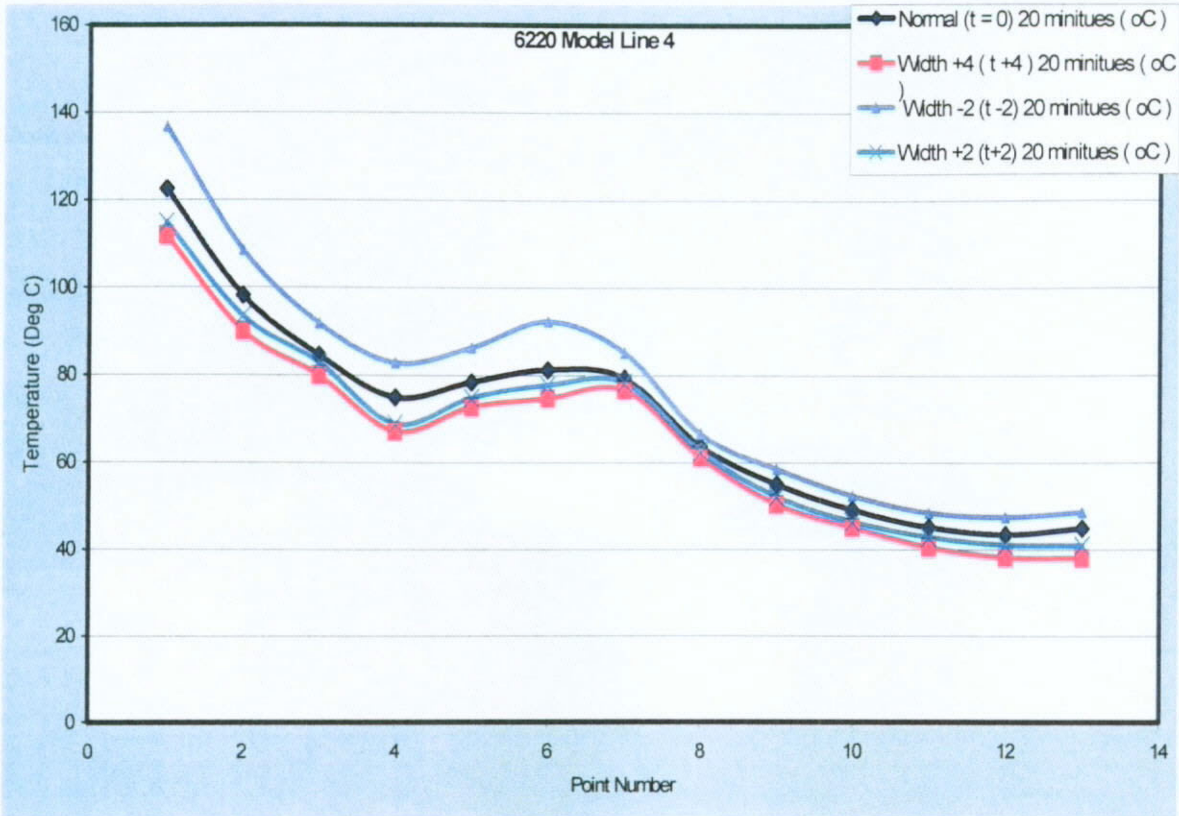


Fig. 110 Experimental Temperature Results of Model 2 (Line 4)

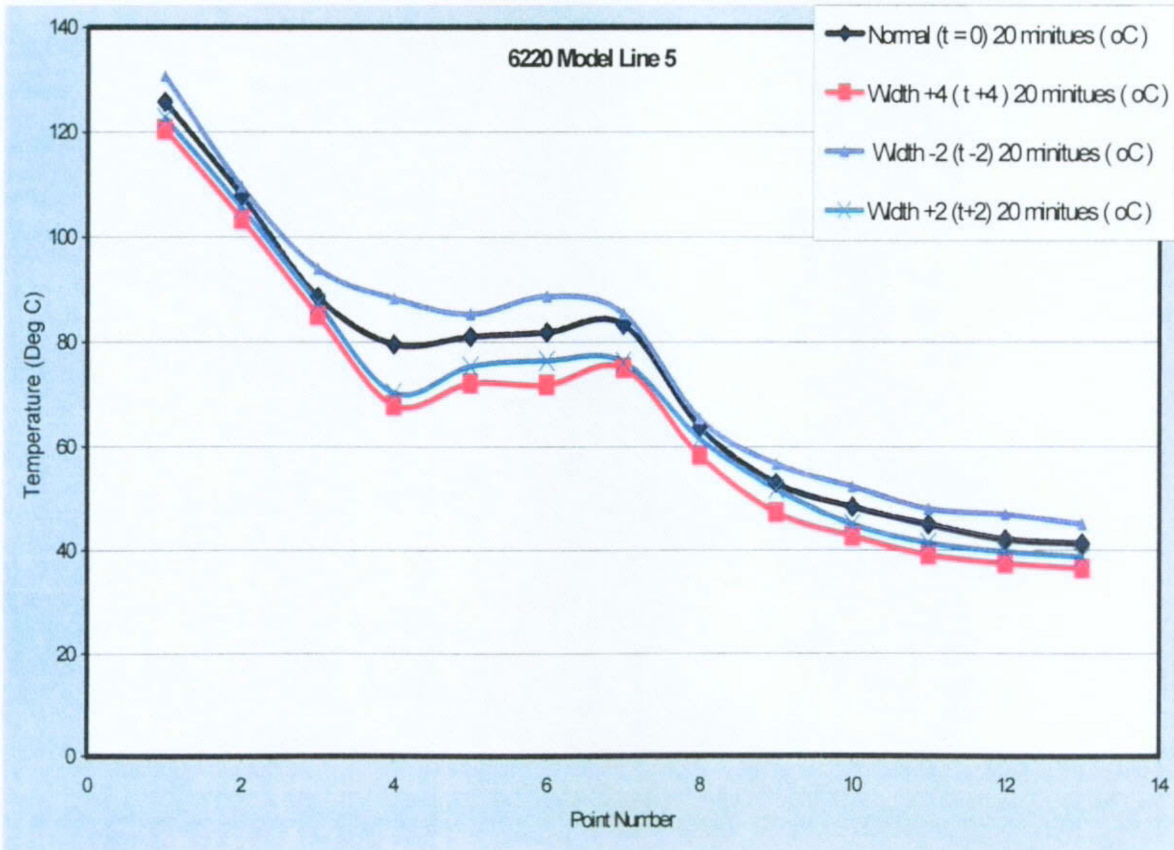


Fig. 111 Experimental Temperature Results of Model 2 (Line 5)

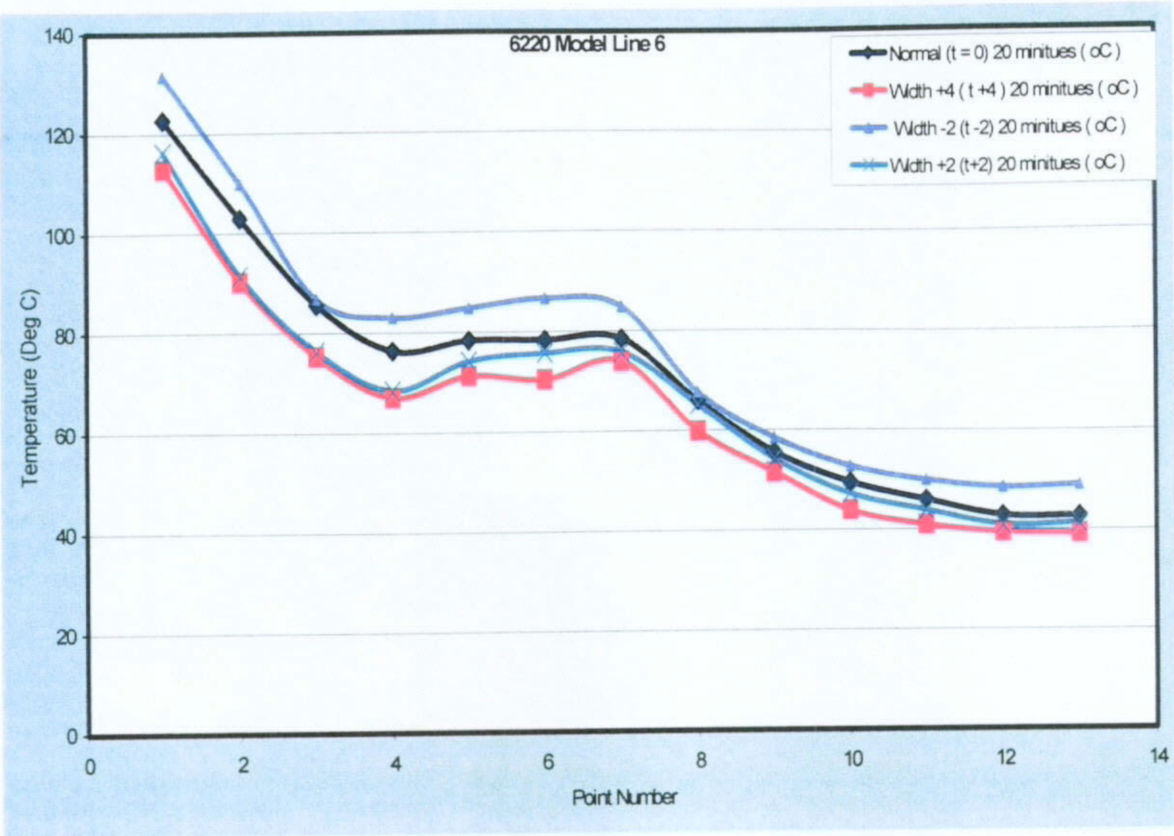


Fig. 112 Experimental Temperature Results of Model 2 (Line 6)

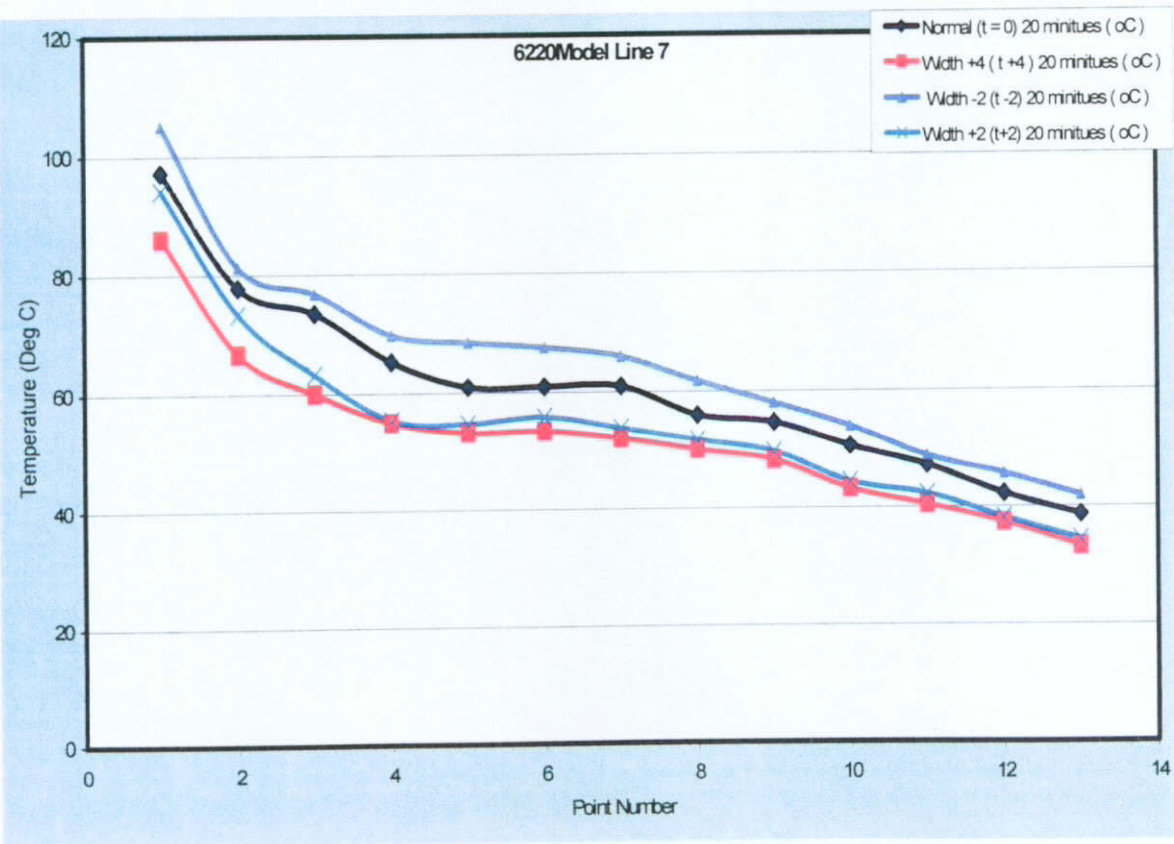


Fig. 113 Experimental Temperature Results of Model 2 (Line 7)

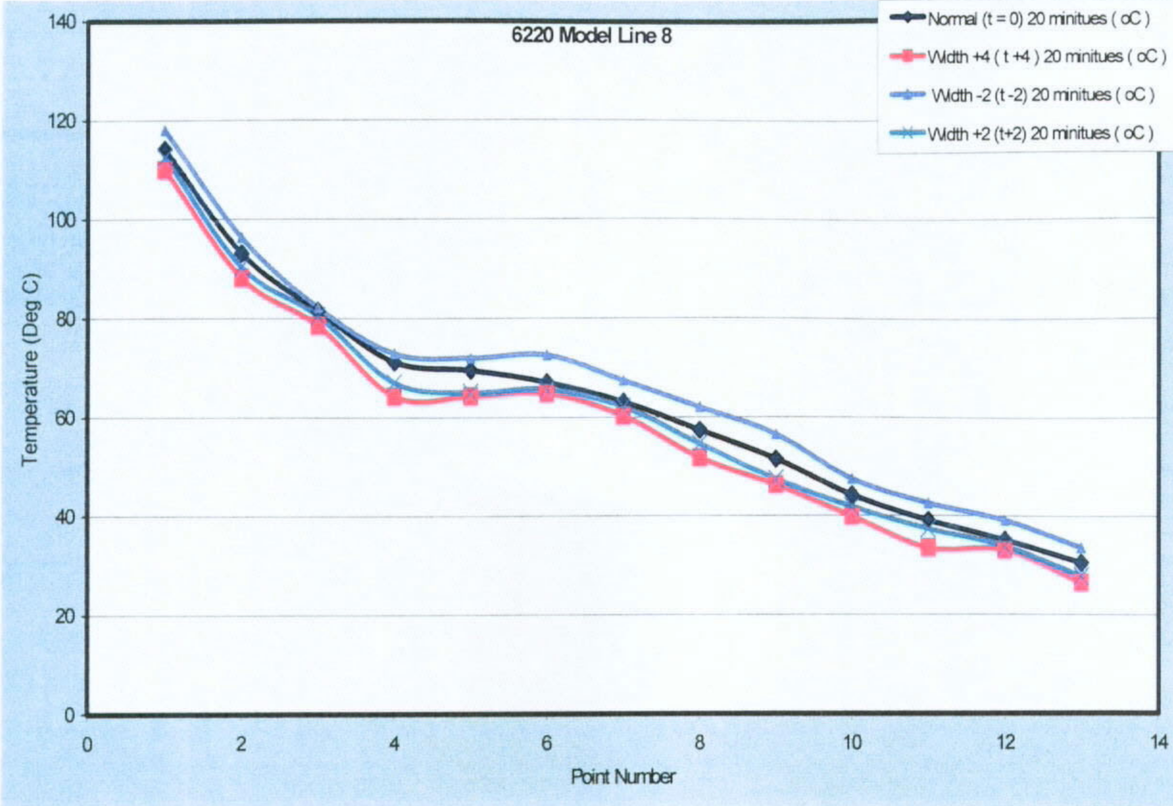


Fig. 114 Experimental Temperature Results of Model 2 (Line 8)

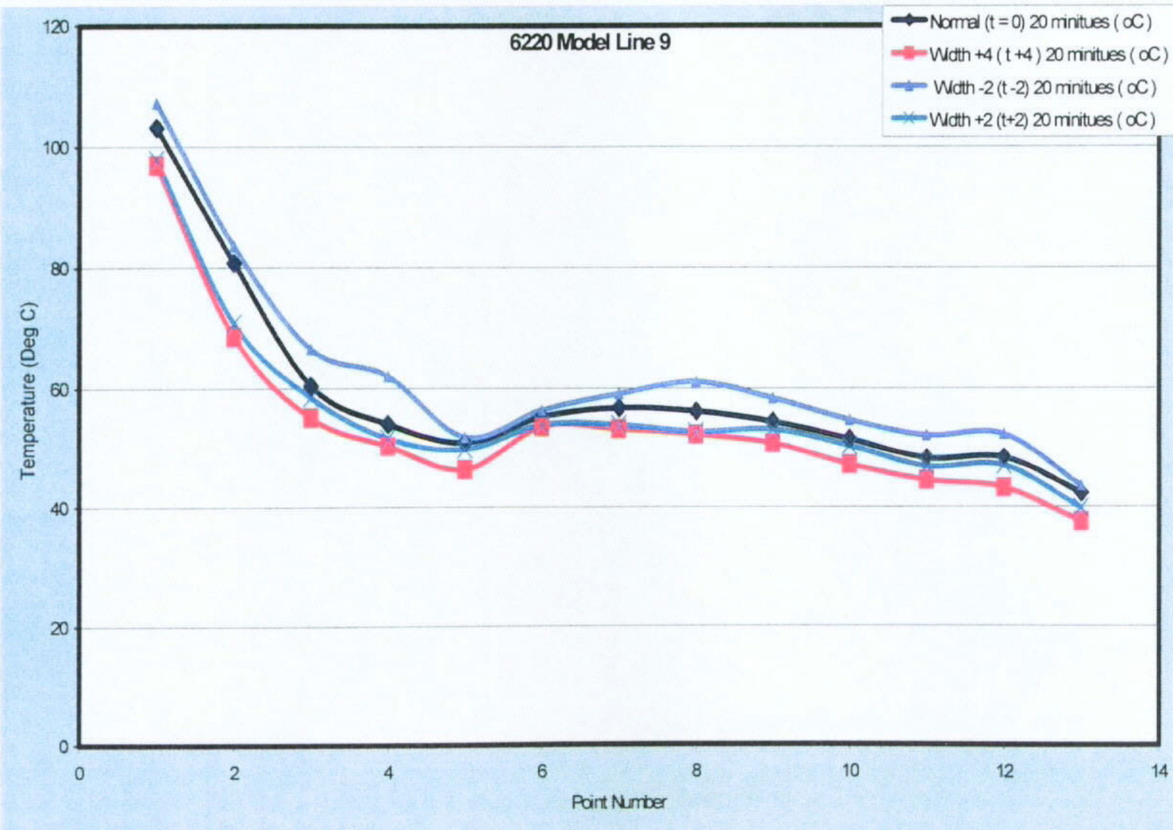


Fig. 115 Experimental Temperature Results of Model 2 (Line 9)

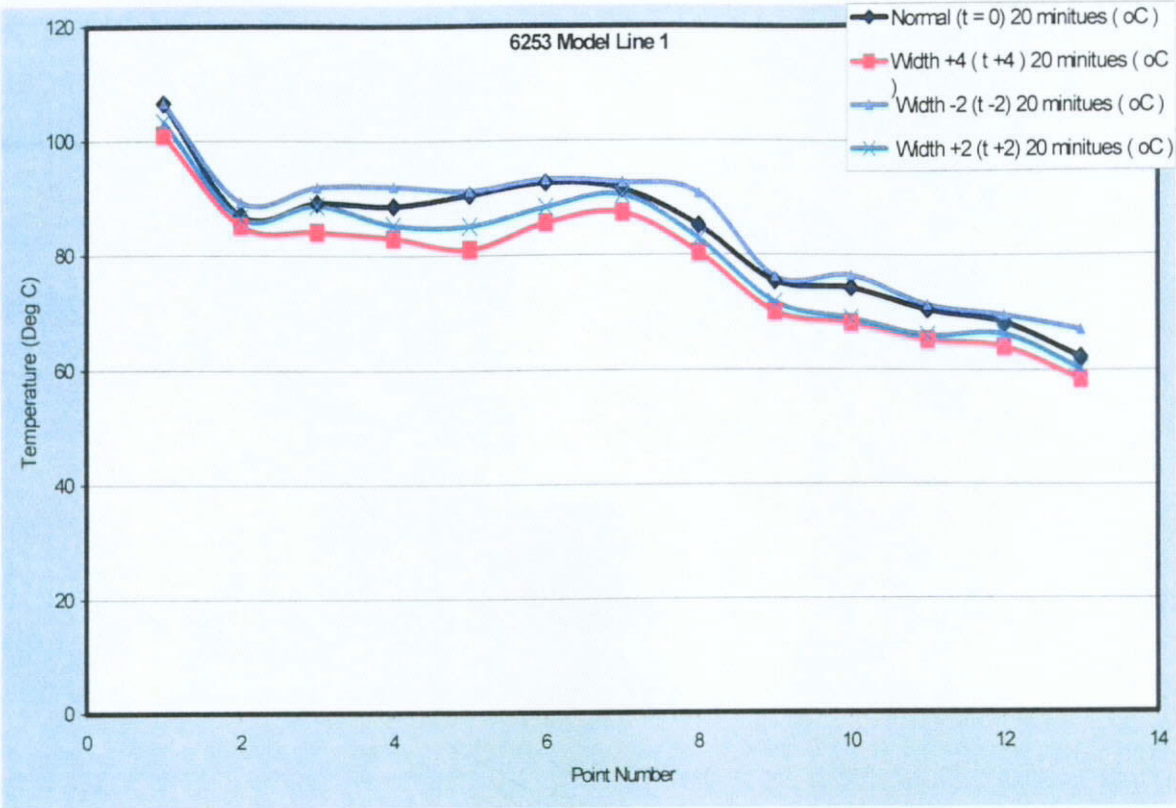


Fig. 116 Experimental Temperature Results of Model 3 (Line 1)

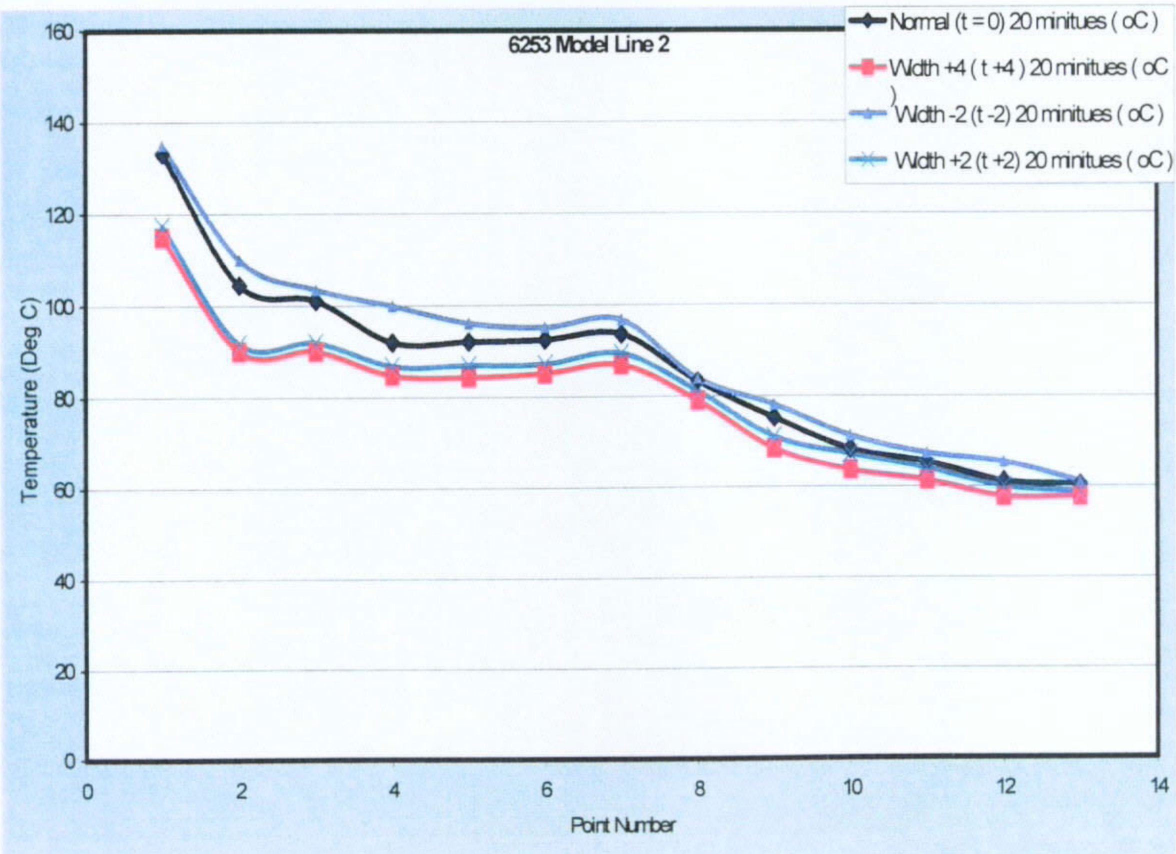


Fig. 117 Experimental Temperature Results of Model 3 (Line 2)

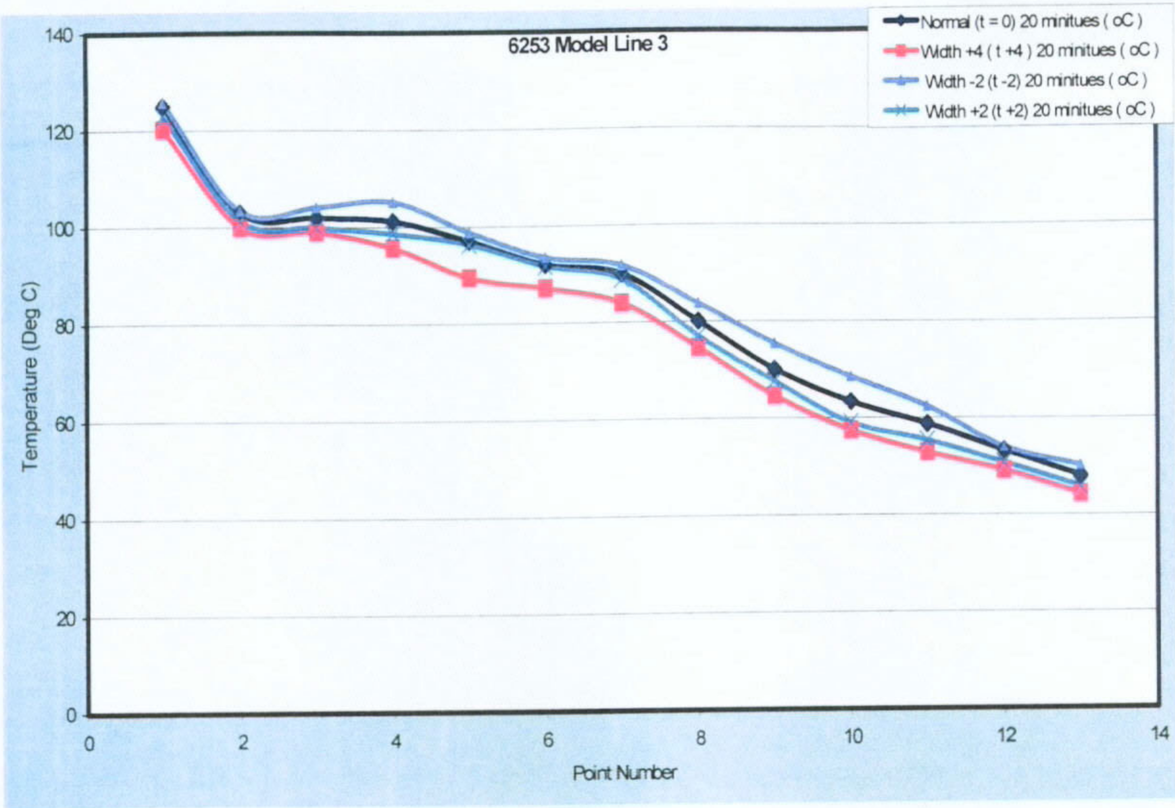


Fig. 118 Experimental Temperature Results of Model 3 (Line 3)

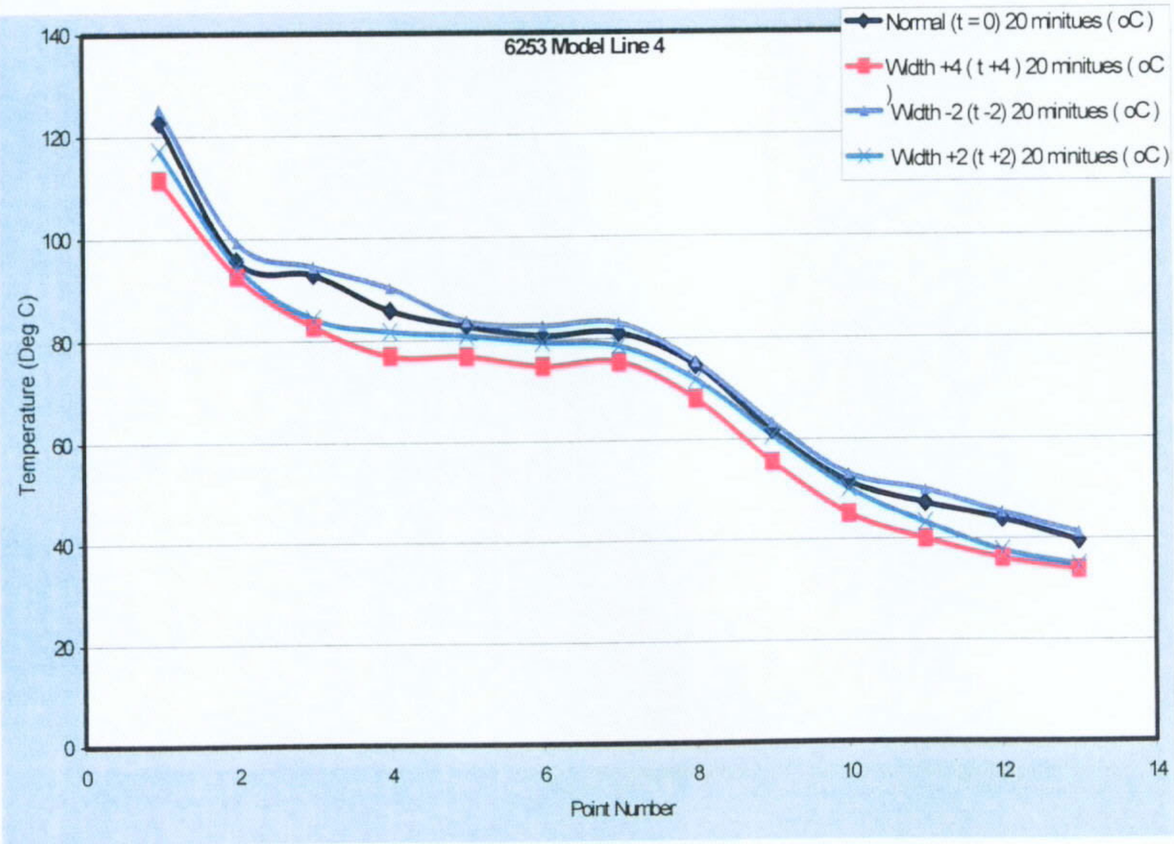


Fig. 119 Experimental Temperature Results of Model 3 (Line 4)

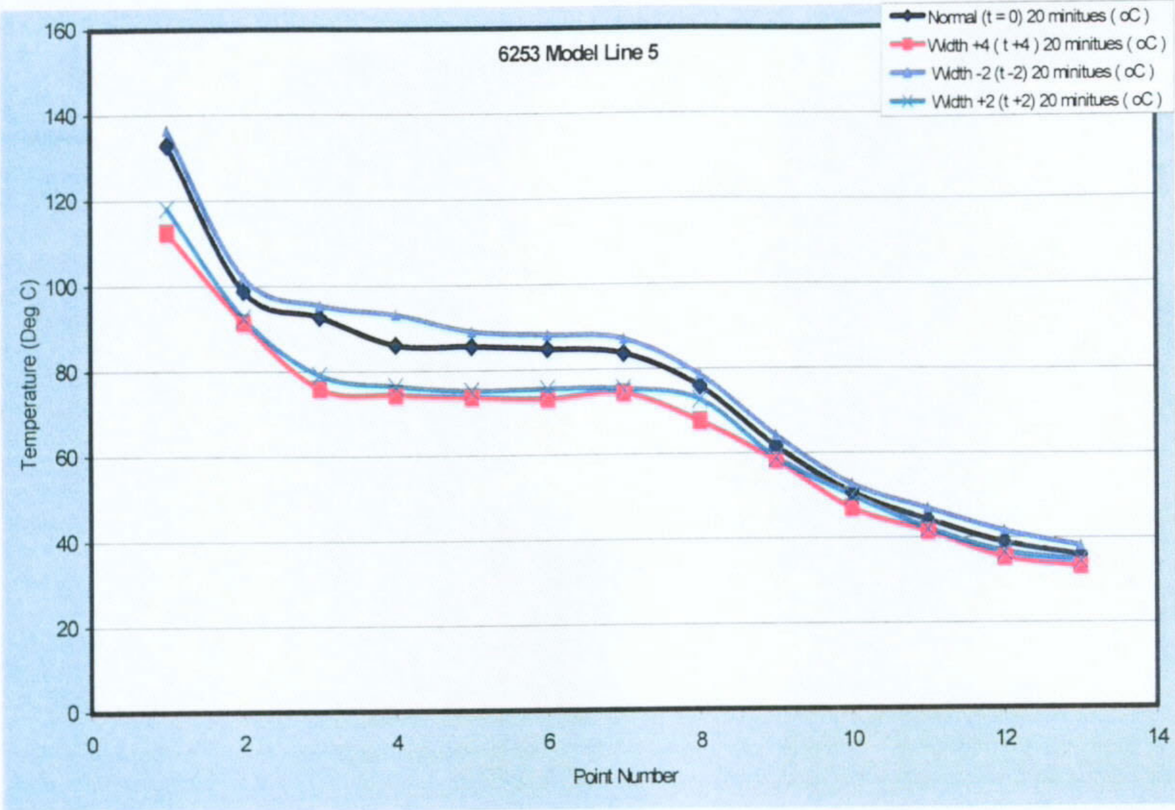


Fig. 120 Experimental Temperature Results of Model 3 (Line 5)

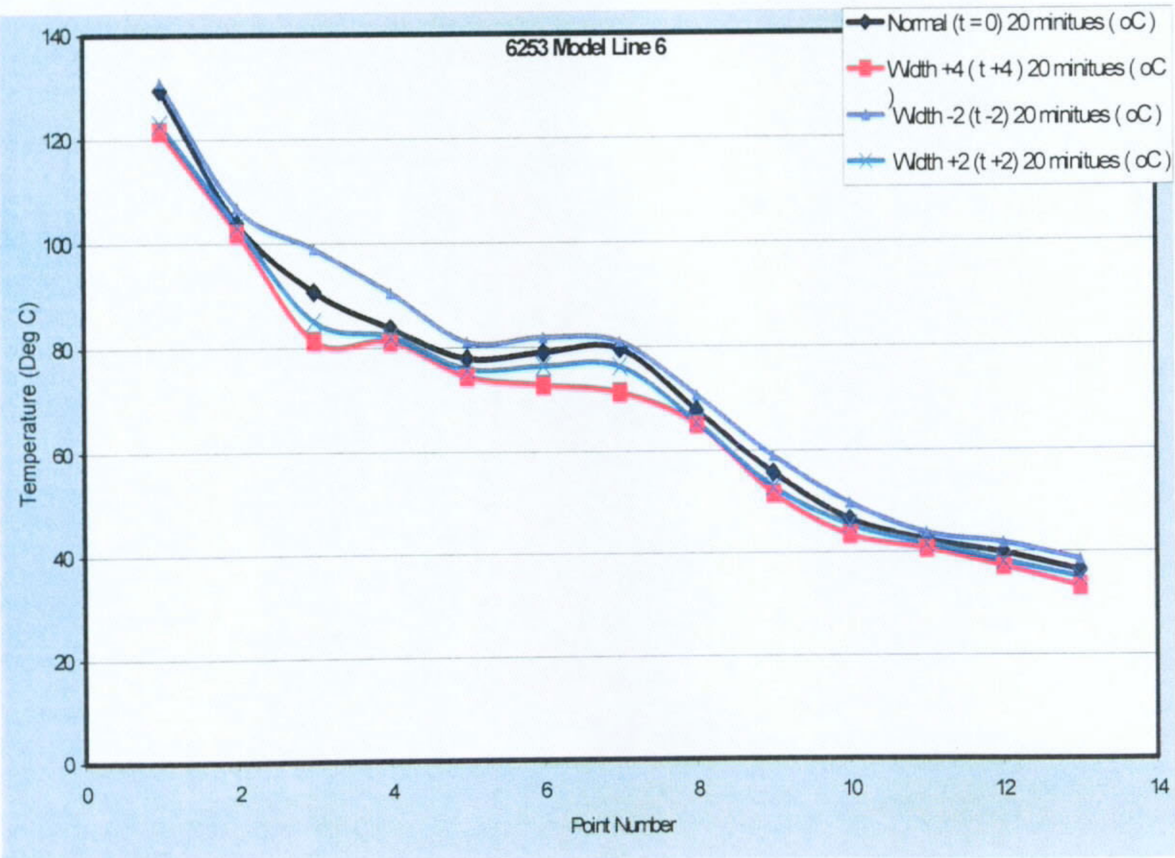


Fig. 121 Experimental Temperature Results of Model 3 (Line 6)

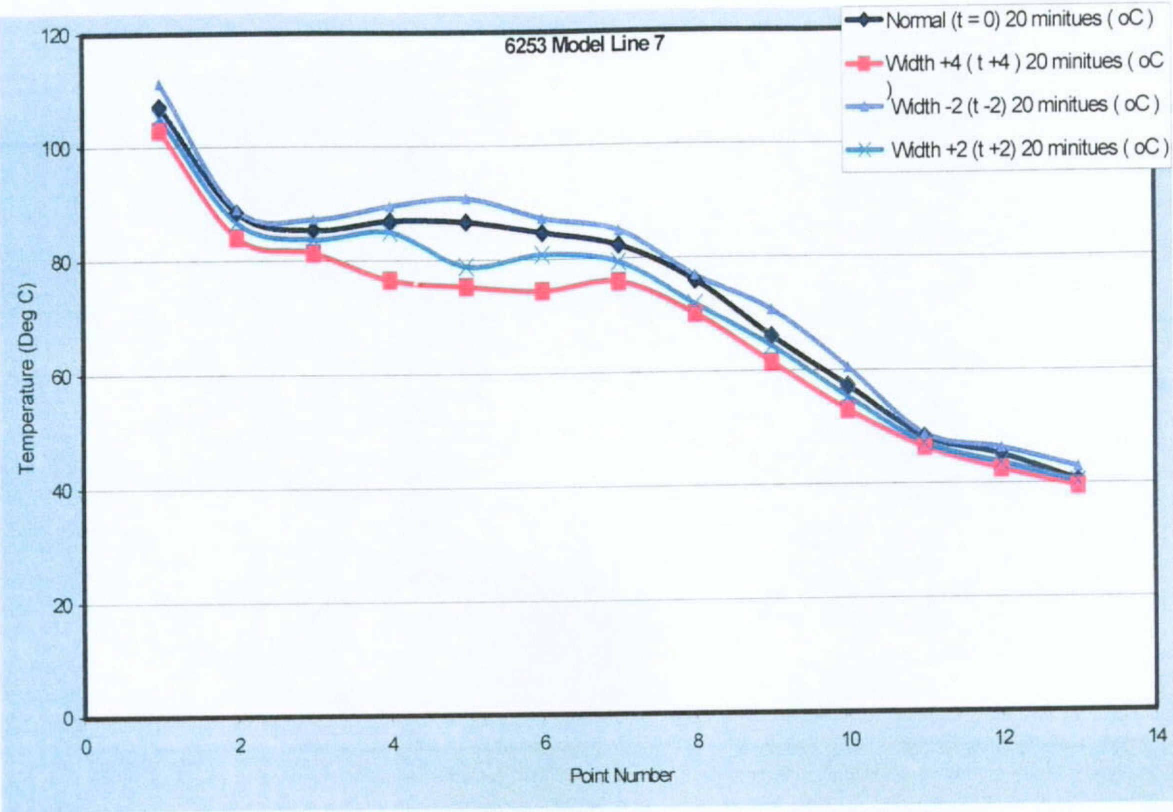


Fig. 122 Experimental Temperature Results of Model 3 (Line 7)

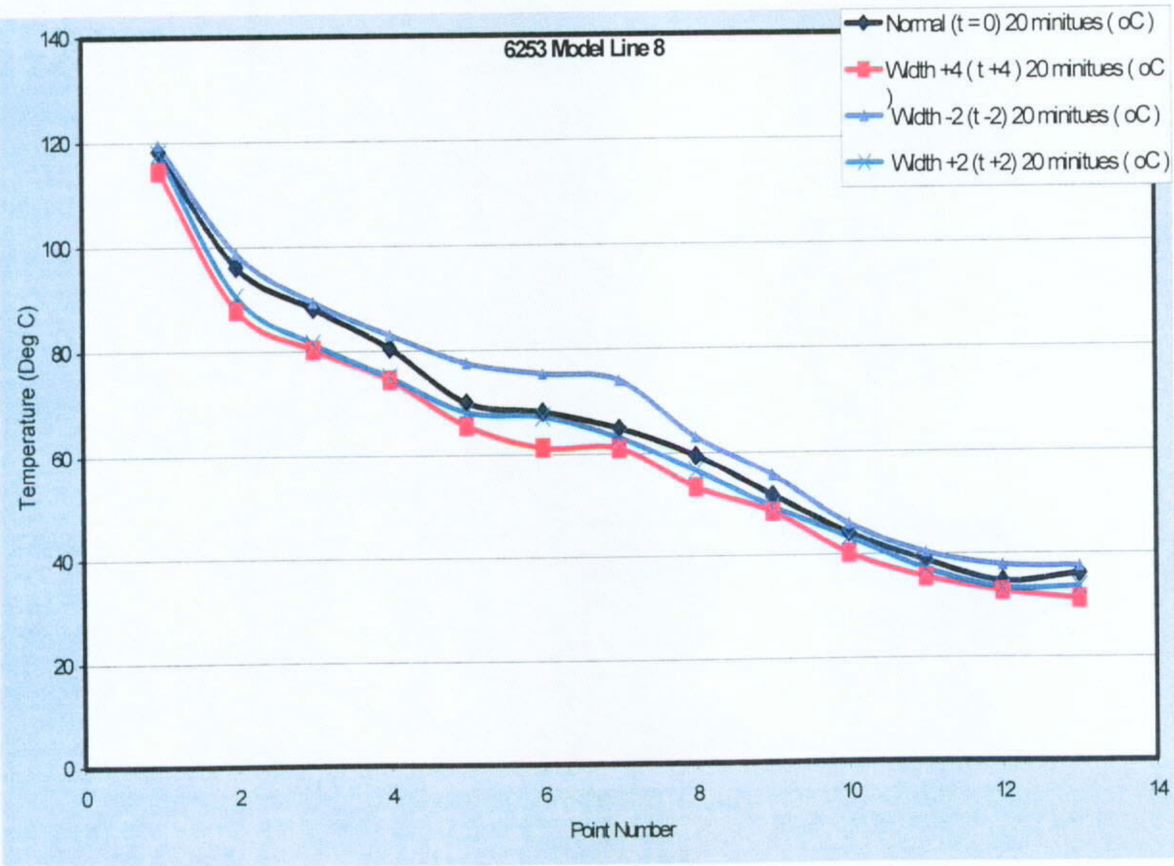


Fig. 123 Experimental Temperature Results of Model 3 (Line 8)

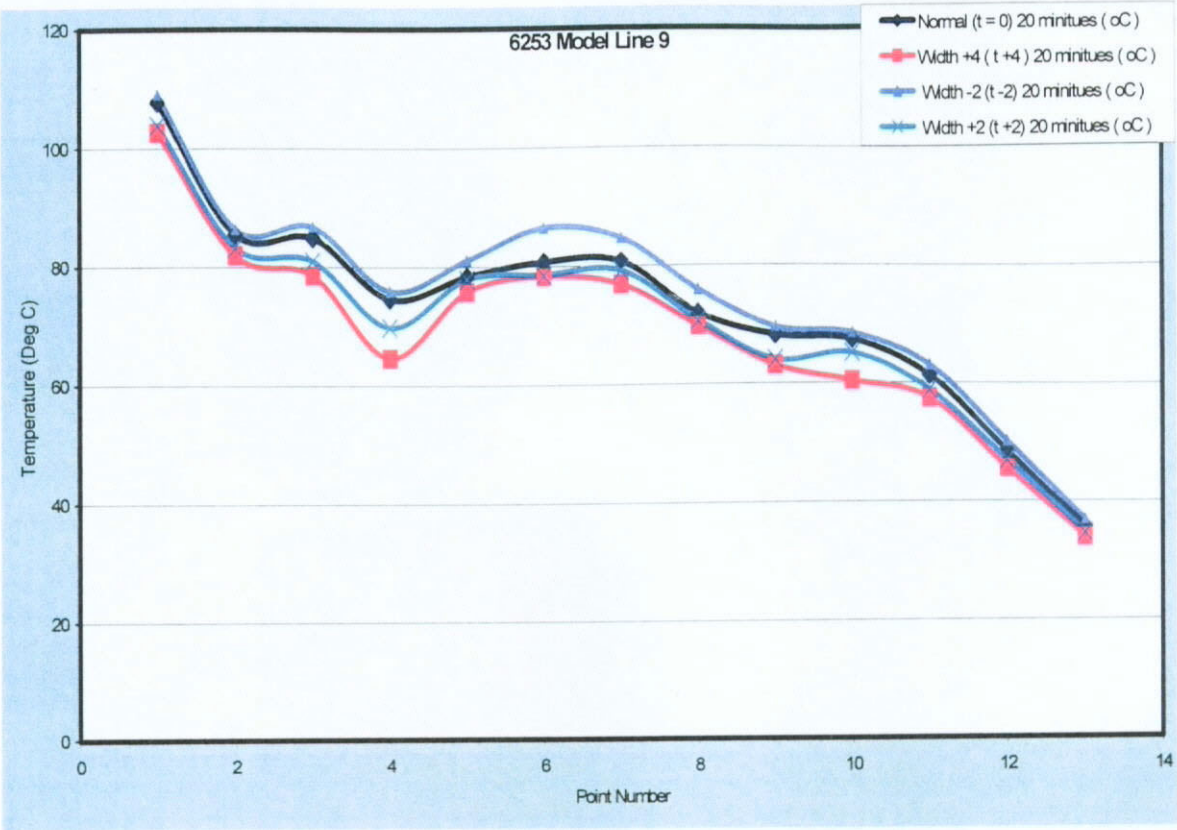


Fig. 124 Experimental Temperature Results of Model 3 (Line 9)

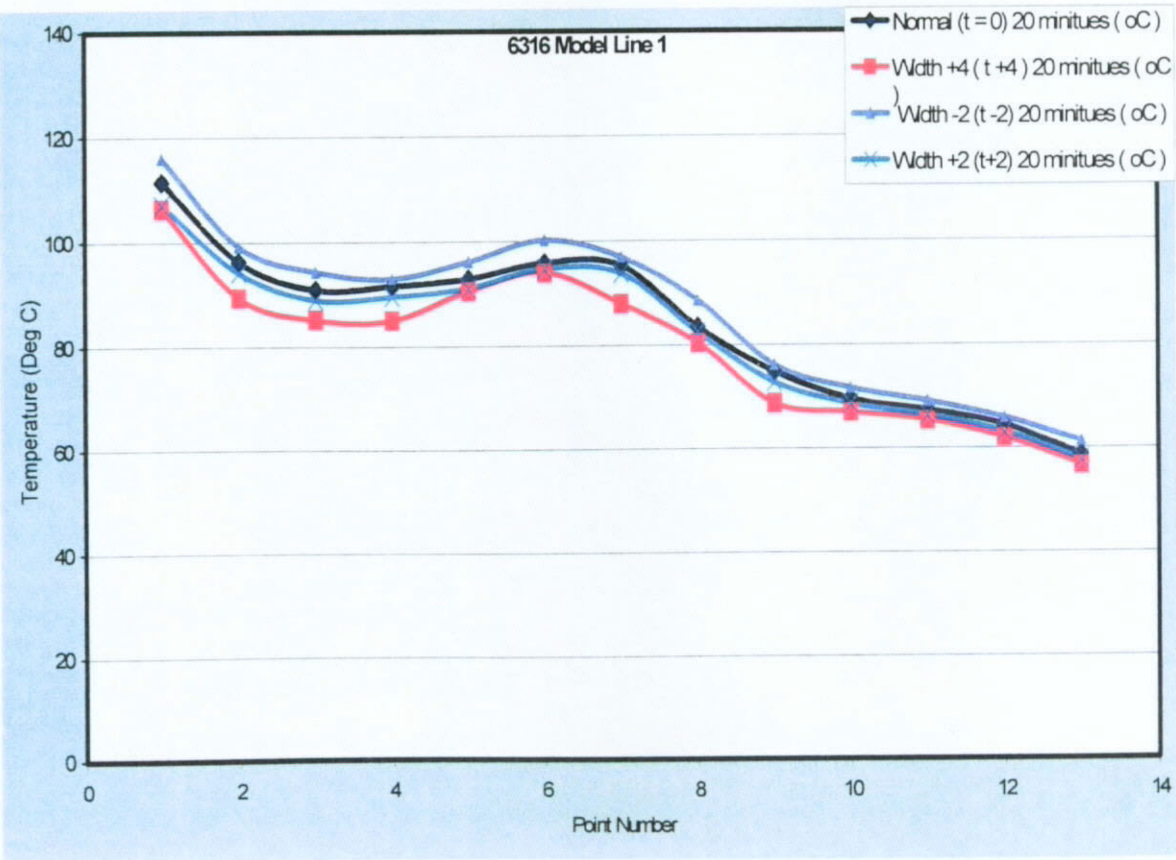


Fig. 125 Experimental Temperature Results of Model 4 (Line 1)

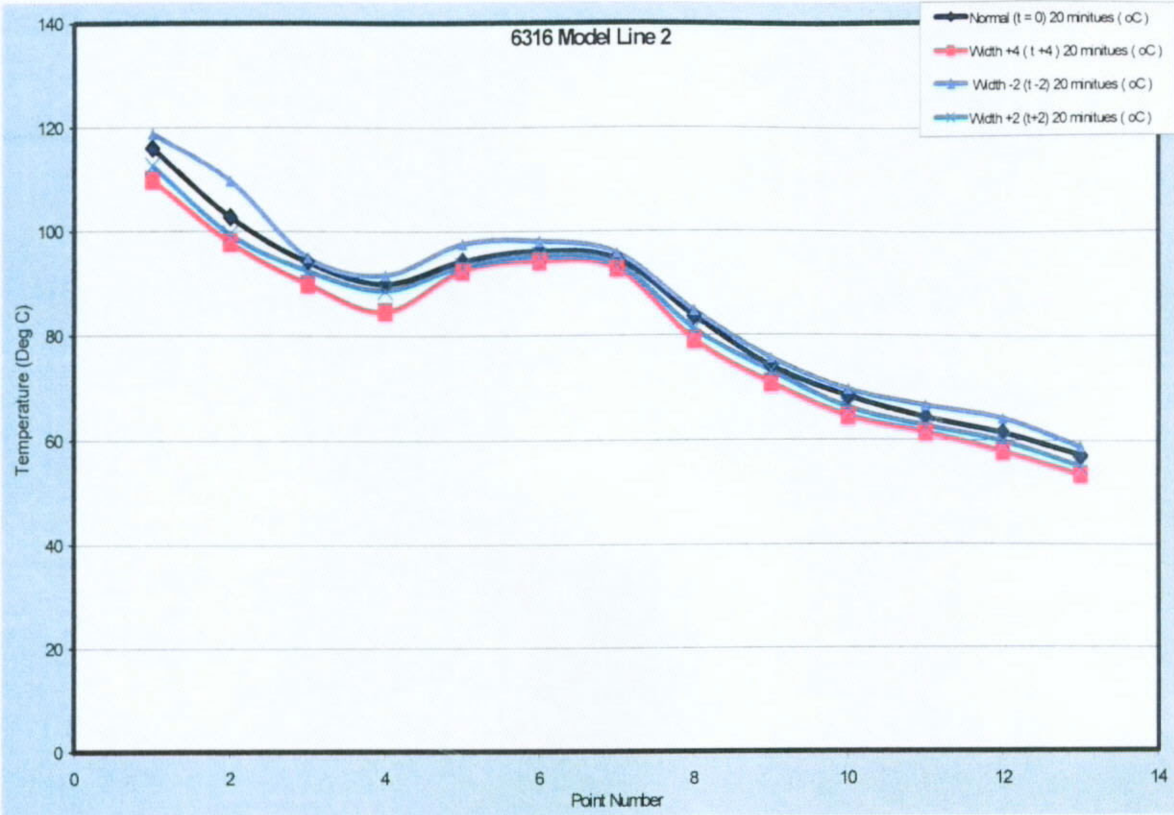


Fig. 126 Experimental Temperature Results of Model 4 (Line 2)

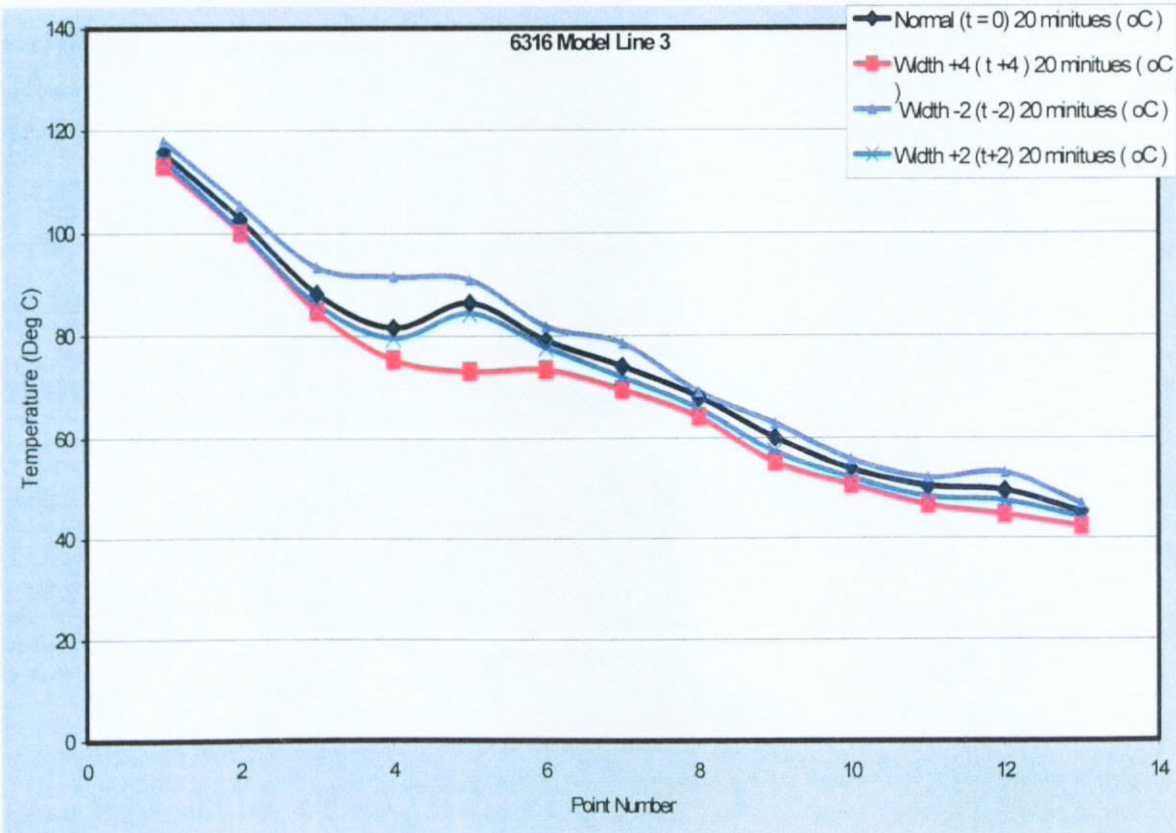


Fig. 127 Experimental Temperature Results of Model 4 (Line 3)

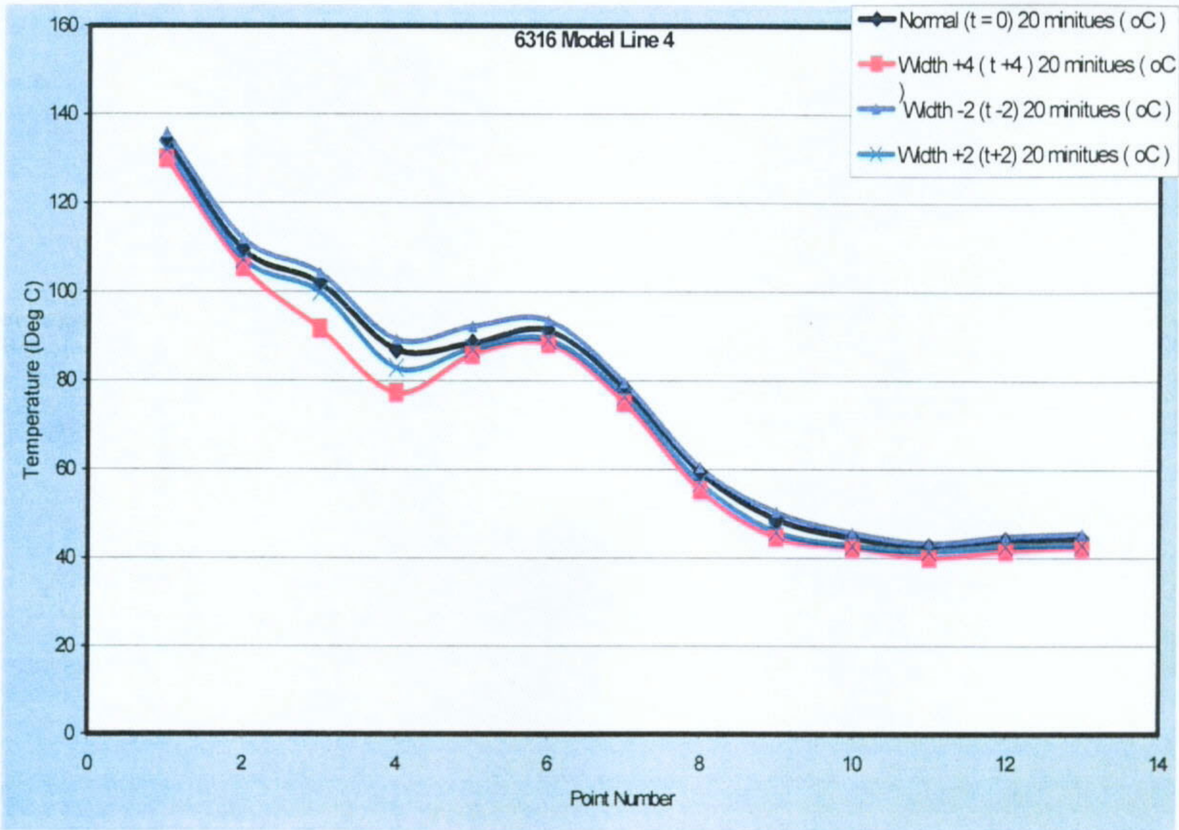


Fig. 128 Experimental Temperature Results of Model 4 (Line 4)

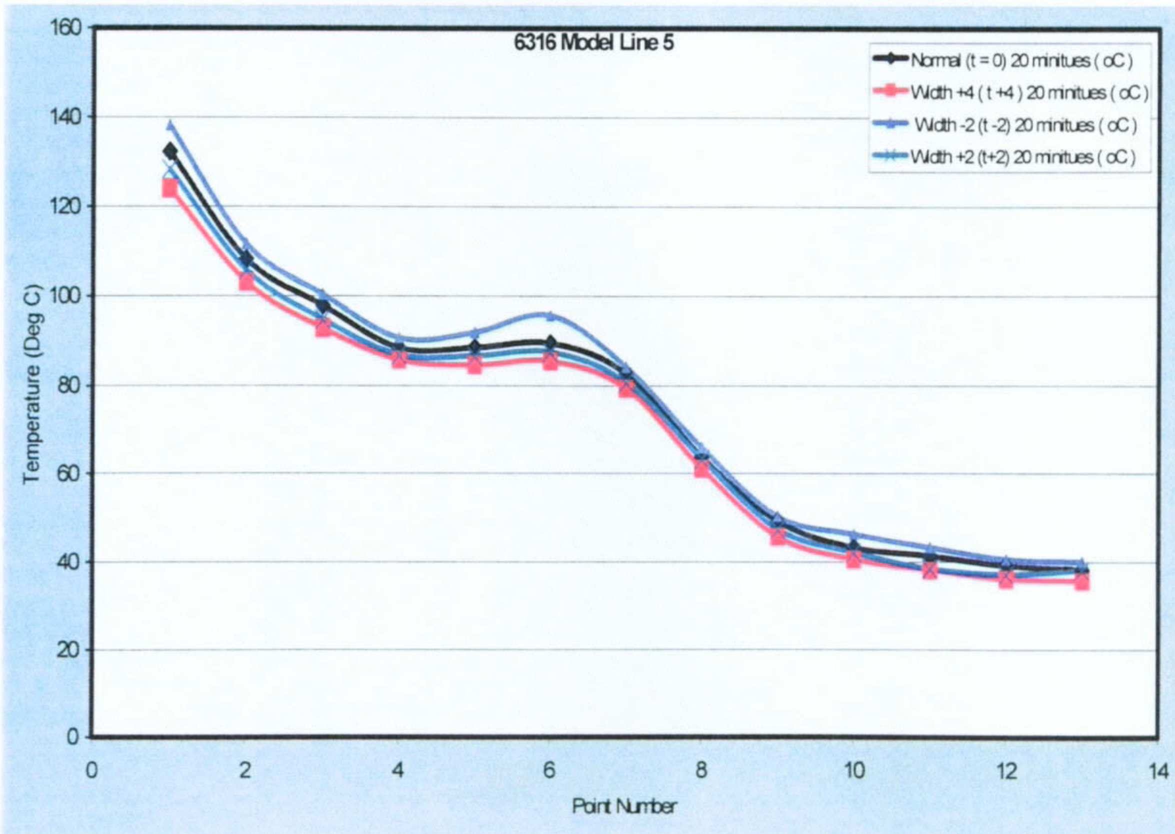


Fig. 129 Experimental Temperature Results of Model 4 (Line 5)

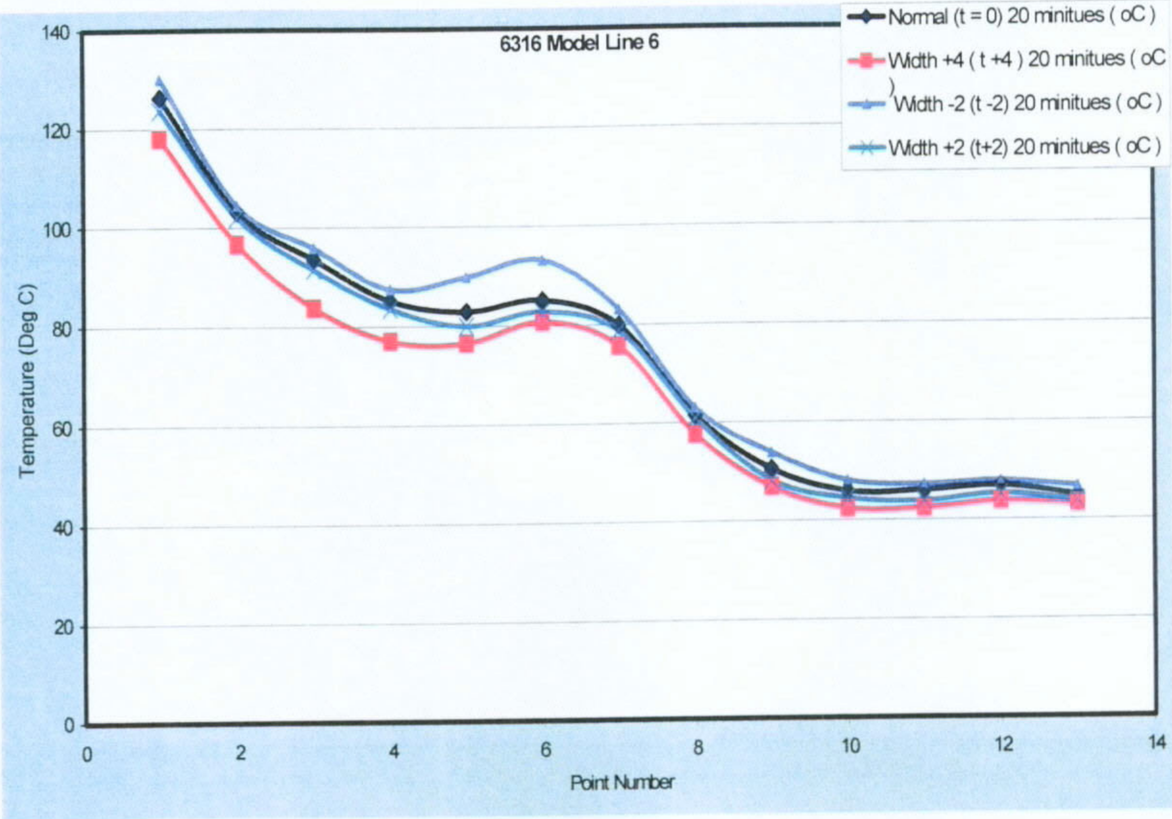


Fig. 130 Experimental Temperature Results of Model 4 (Line 6)

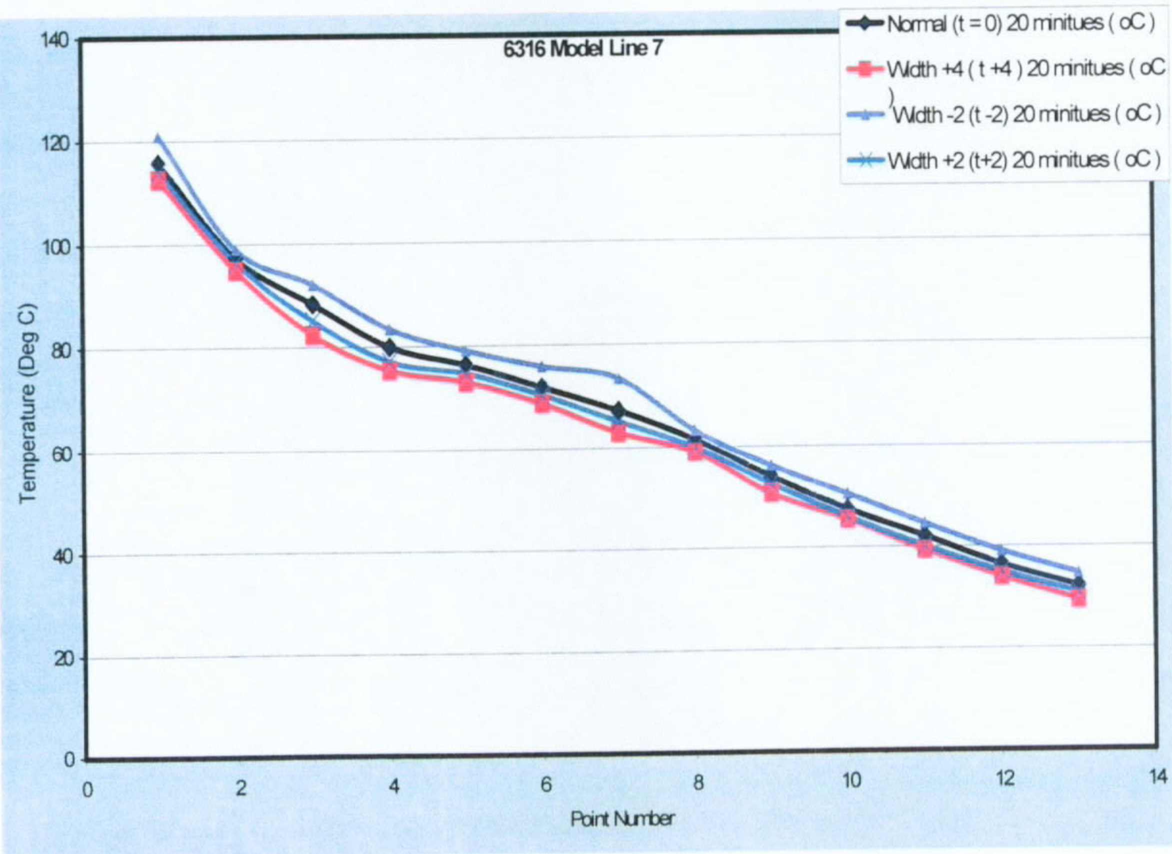


Fig. 131 Experimental Temperature Results of Model 4 (Line 7)

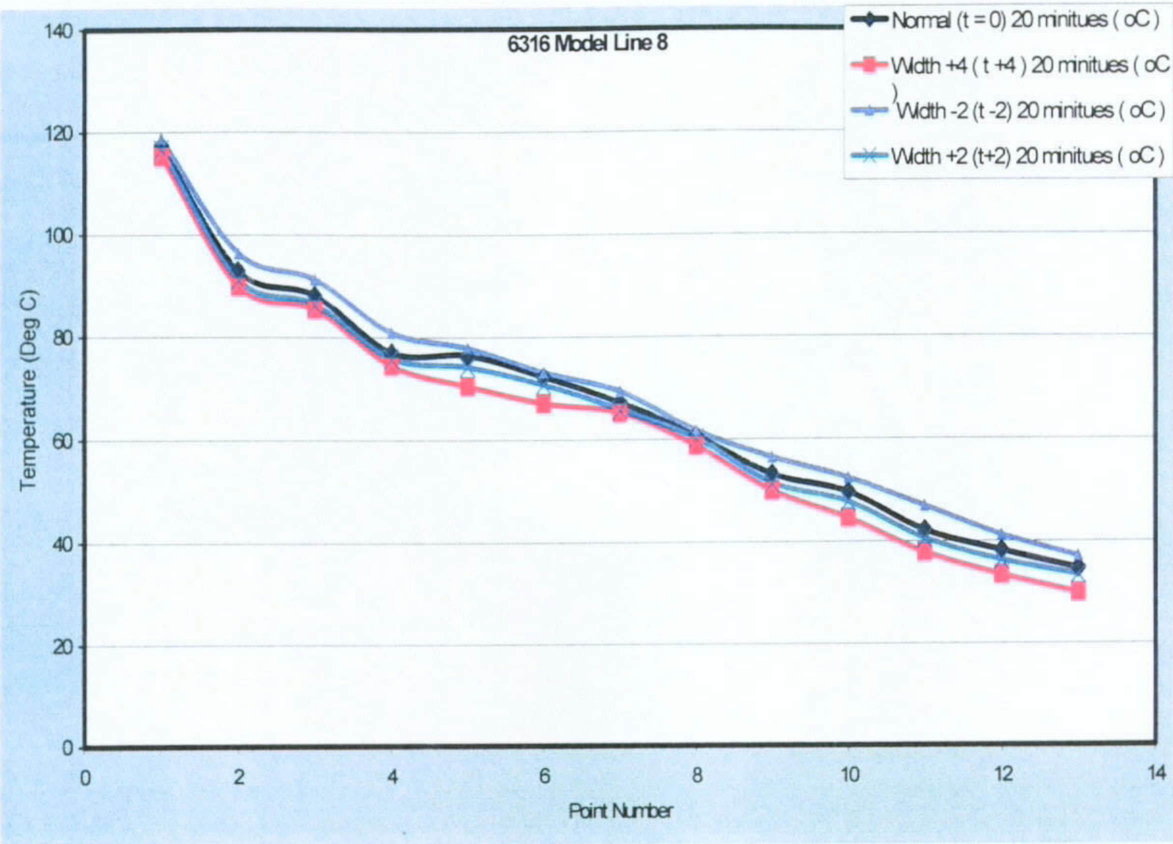


Fig. 132 Experimental Temperature Results of Model 4 (Line 8)

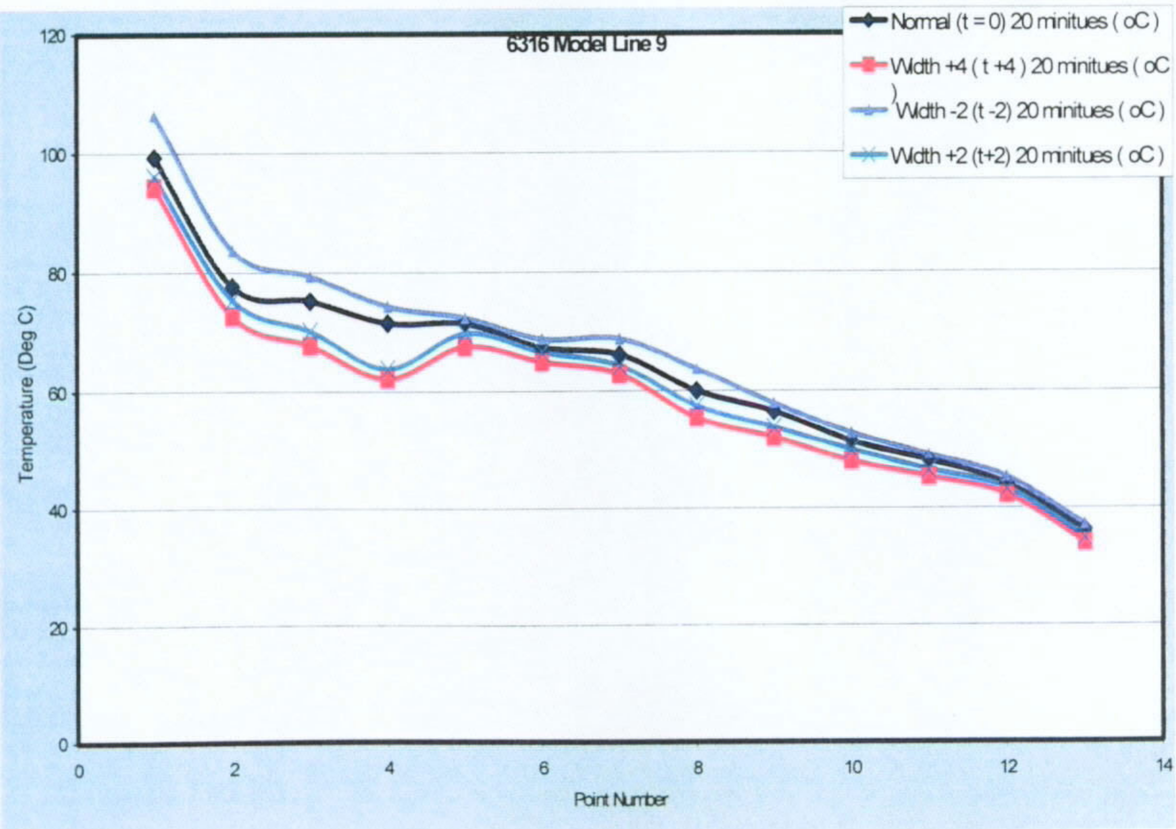


Fig. 133 Experimental Temperature Results of Model 4 (Line 9)

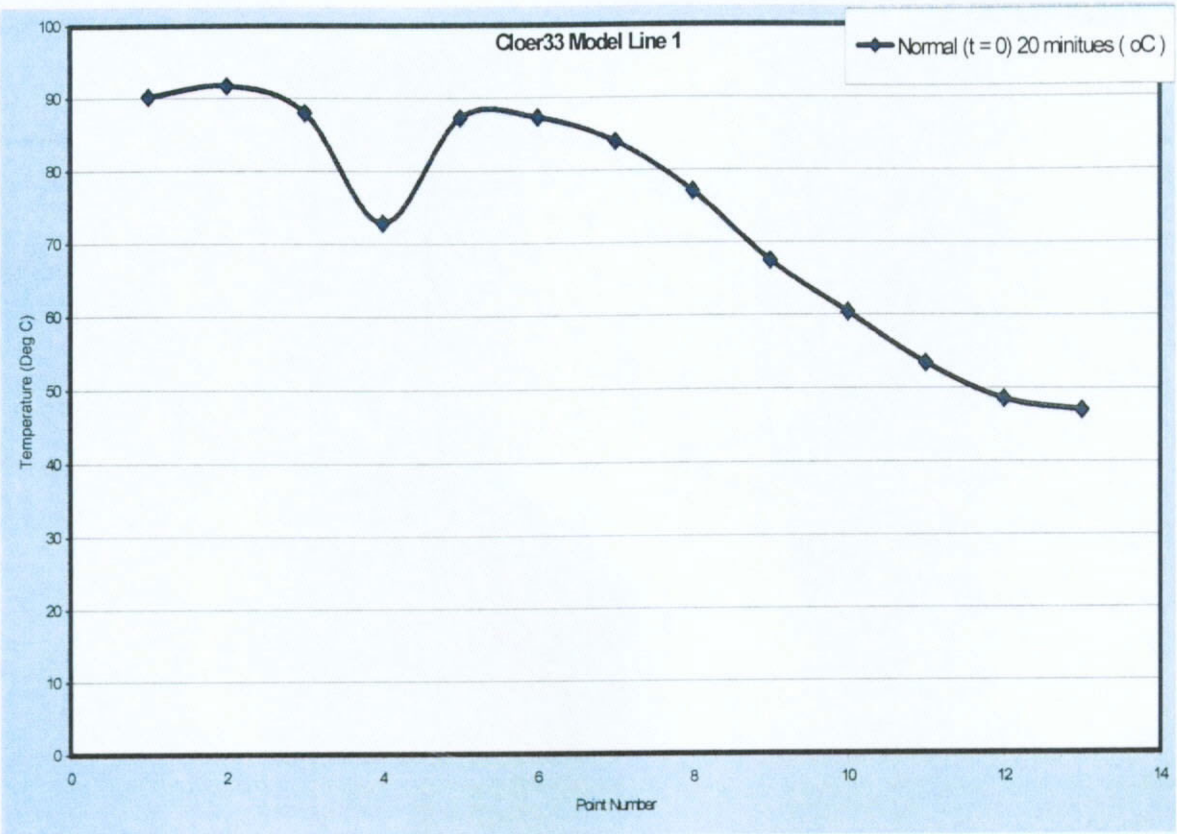


Fig. 134 Experimental Temperature Results of Model 5 (Line 1)

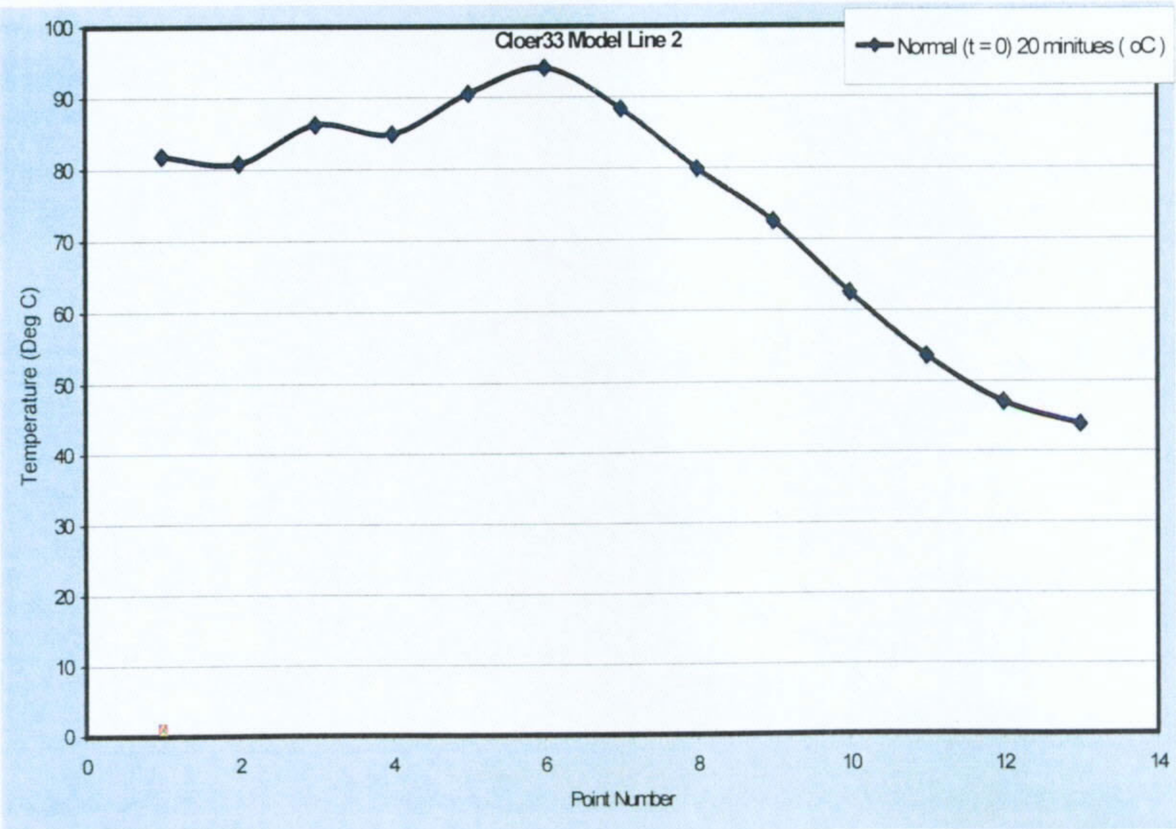


Fig. 135 Experimental Temperature Results of Model 5 (Line 2)

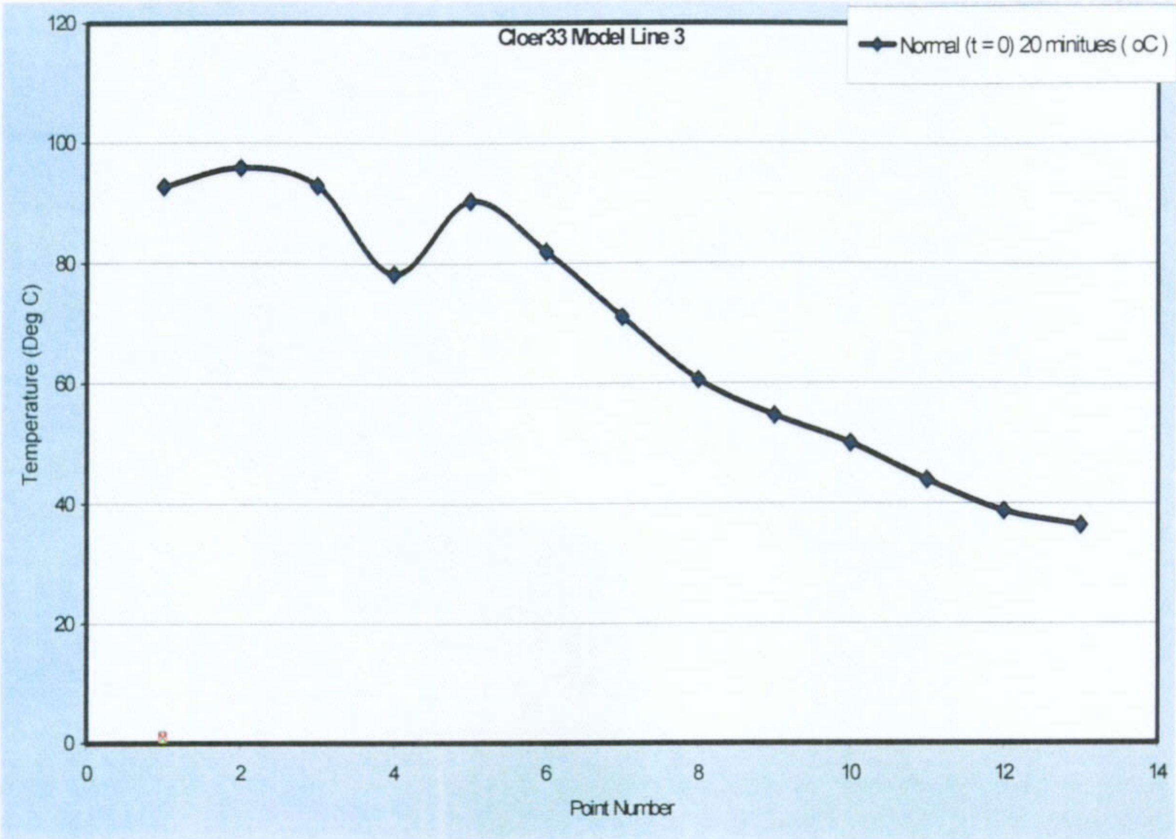


Fig. 136 Experimental Temperature Results of Model 5 (Line 3)

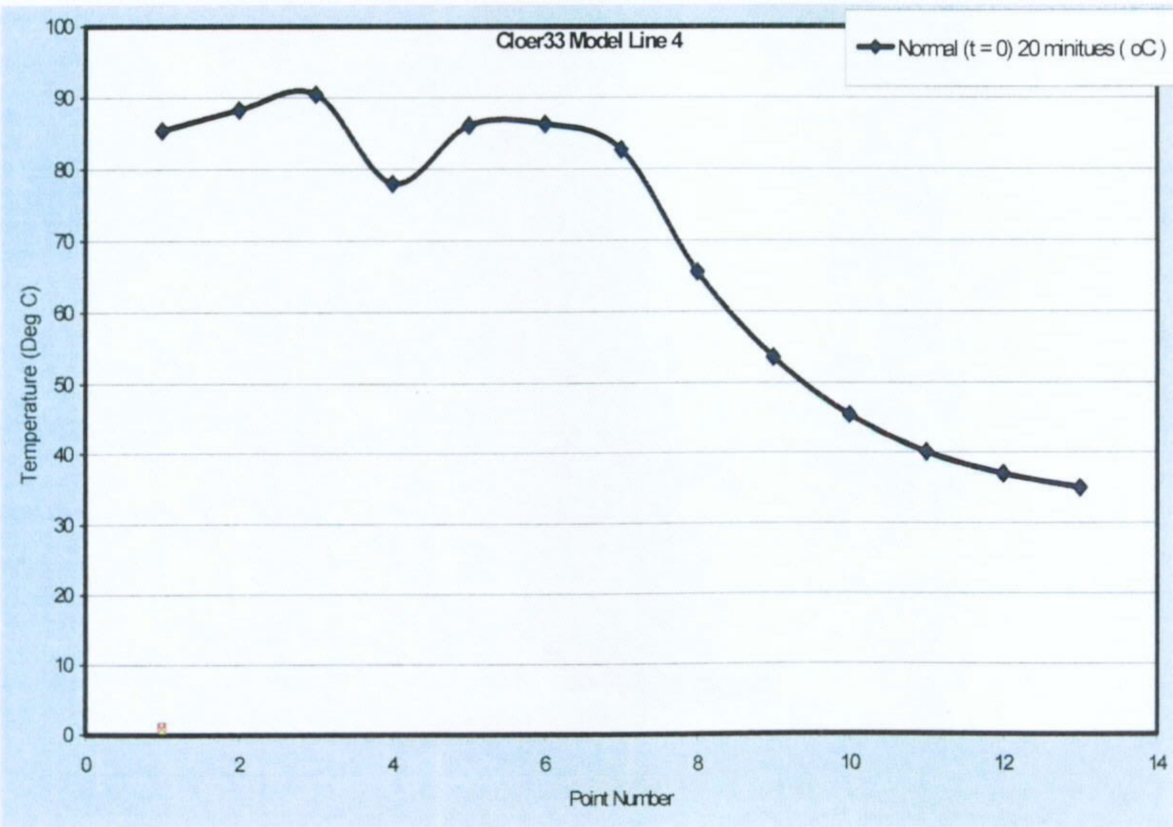


Fig. 137 Experimental Temperature Results of Model 5 (Line 4)

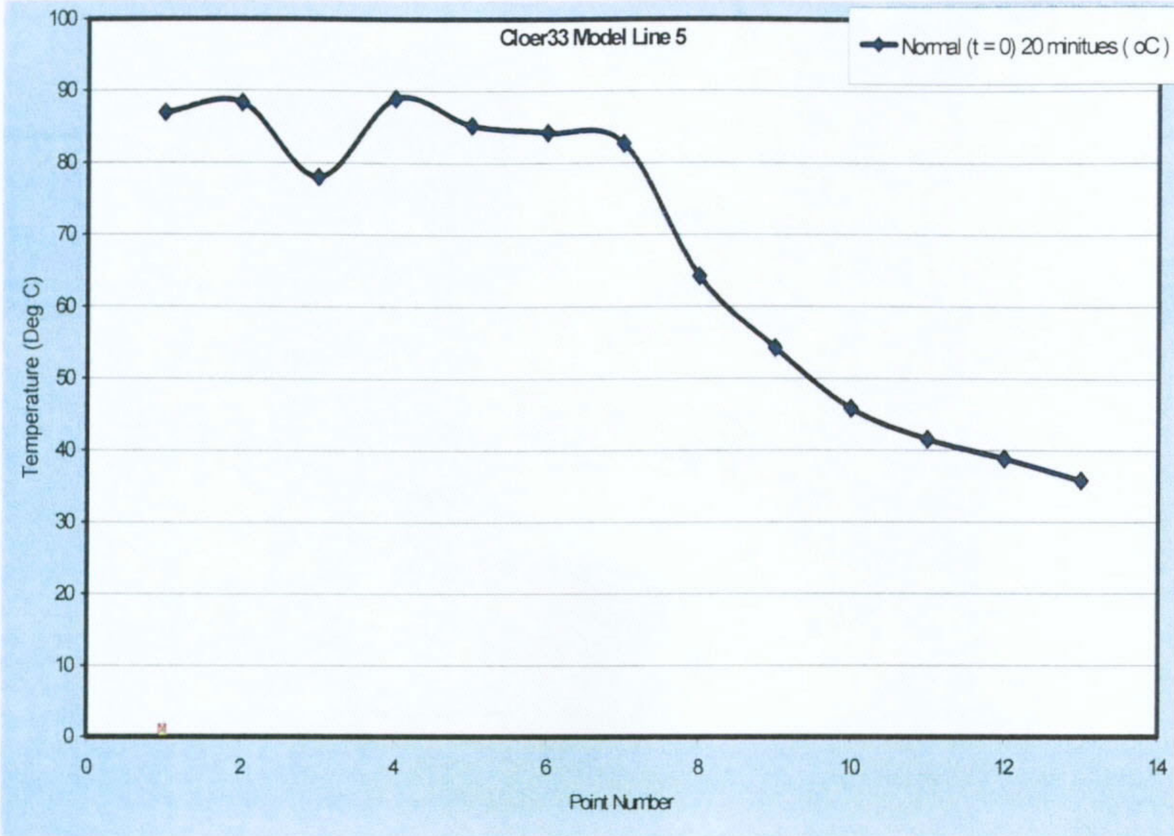


Fig. 138 Experimental Temperature Results of Model 5 (Line 5)

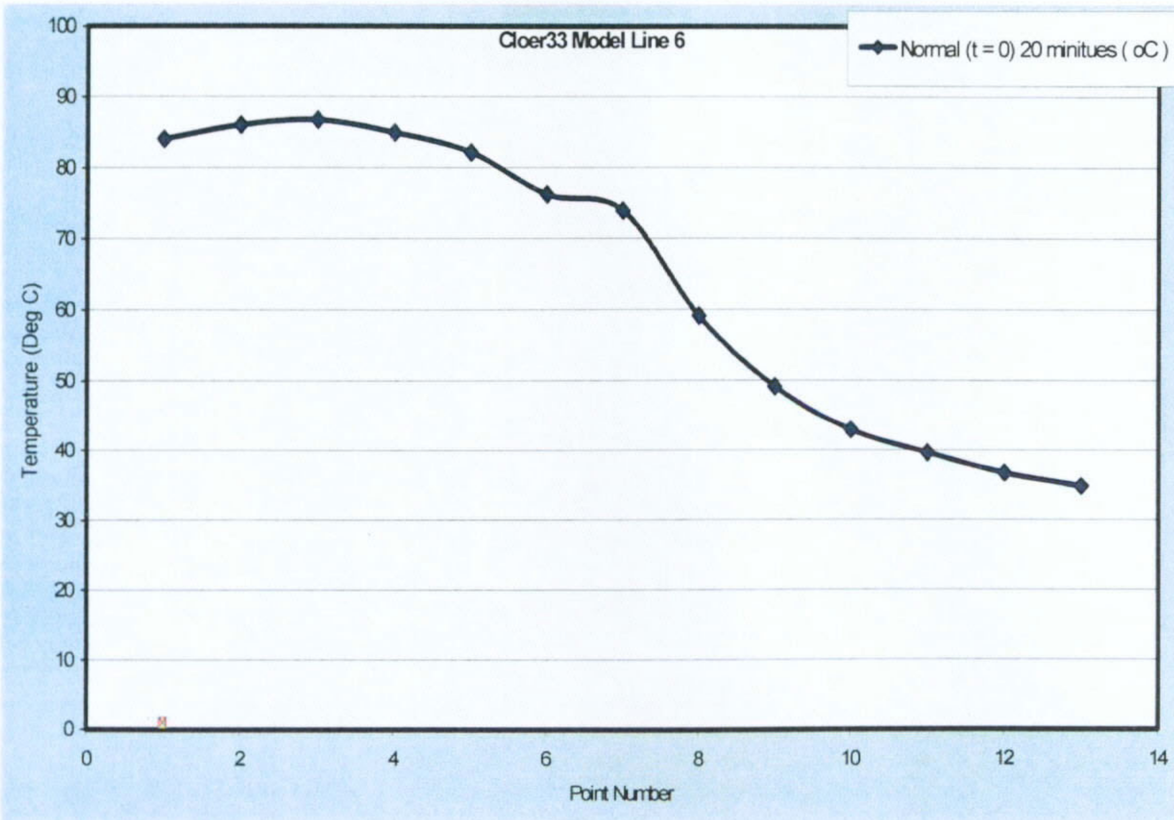


Fig. 139 Experimental Temperature Results of Model 5 (Line 6)

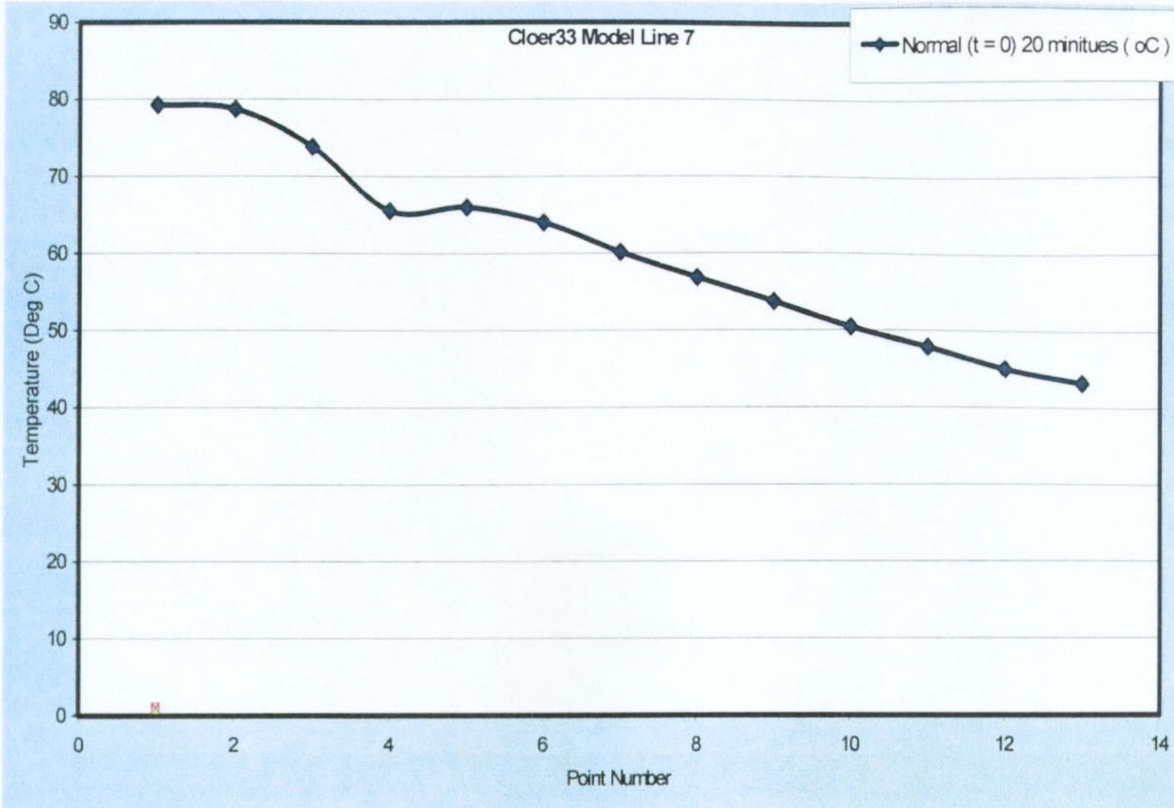


Fig. 140 Experimental Temperature Results of Model 5 (Line 7)

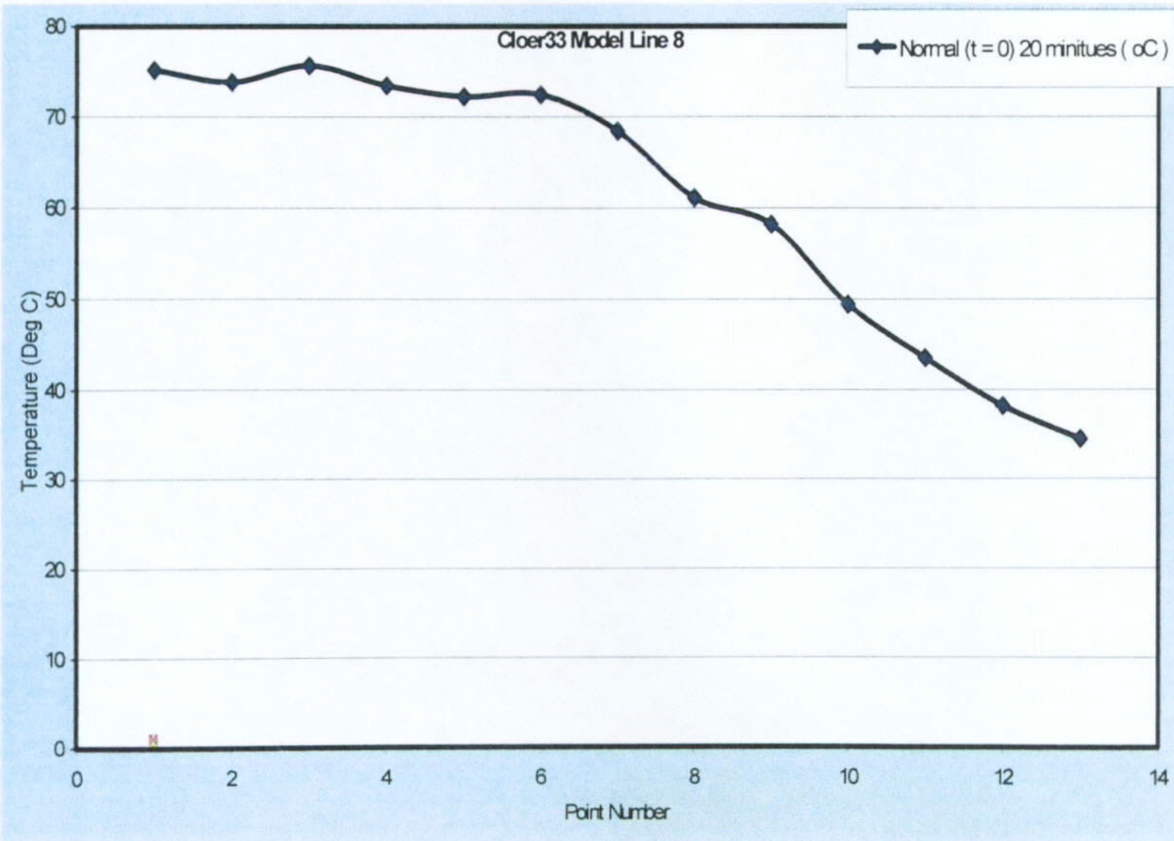


Fig. 141 Experimental Temperature Results of Model 5 (Line 8)

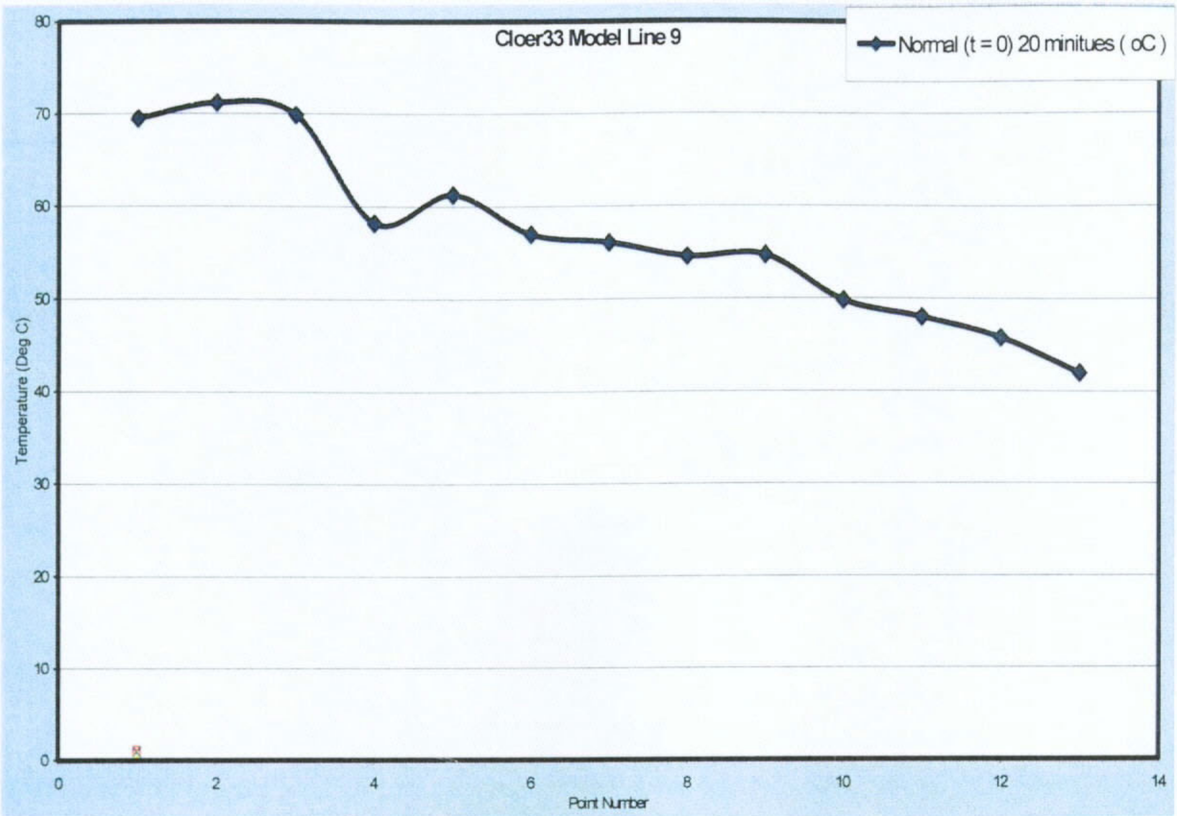


Fig. 142 Experimental Temperature Results of Model 5 (Line 9)

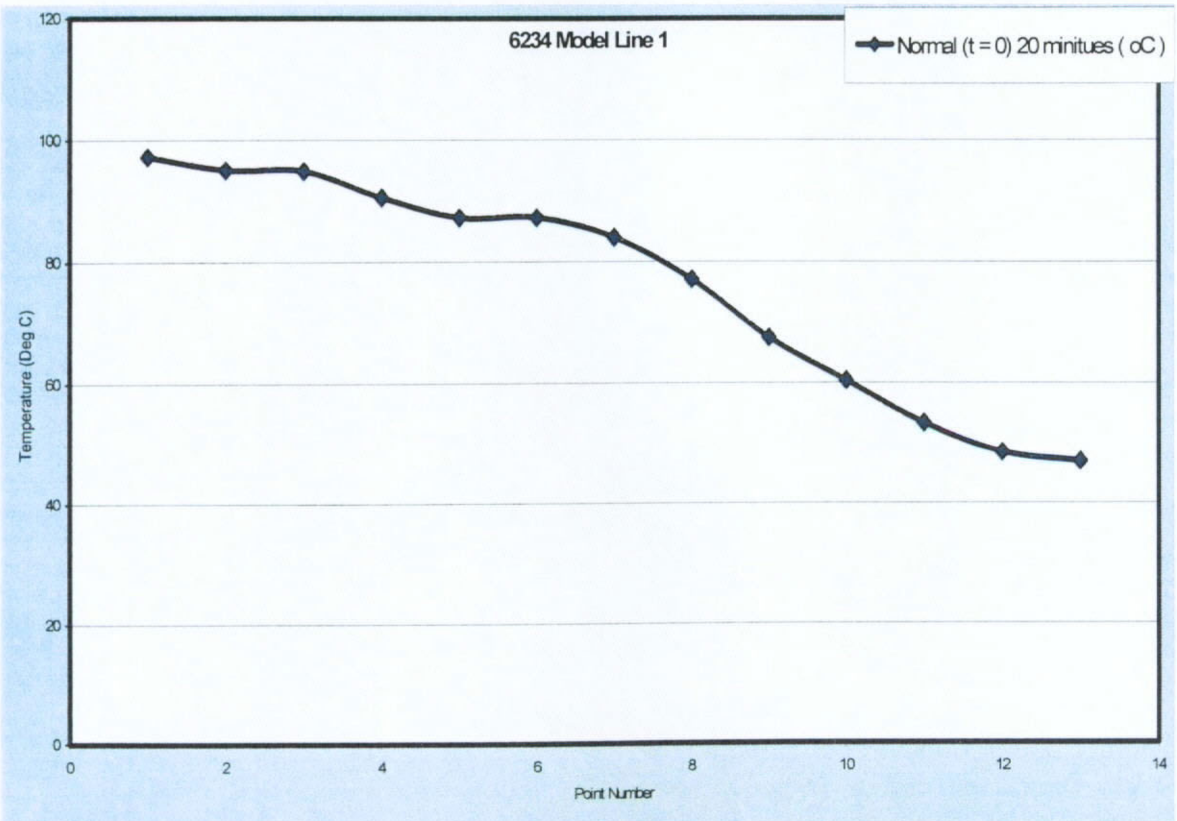


Fig. 143 Experimental Temperature Results of Model 6 (Line 1)

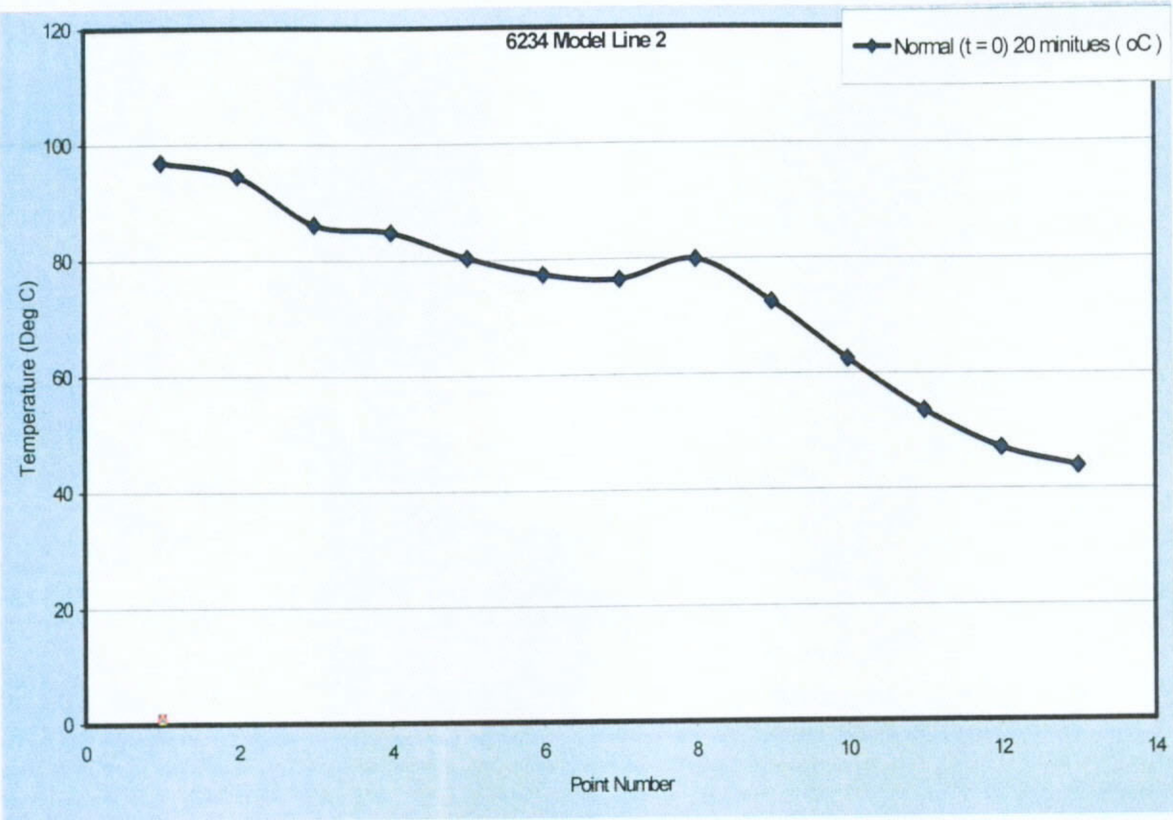


Fig. 144 Experimental Temperature Results of Model 6 (Line 2)

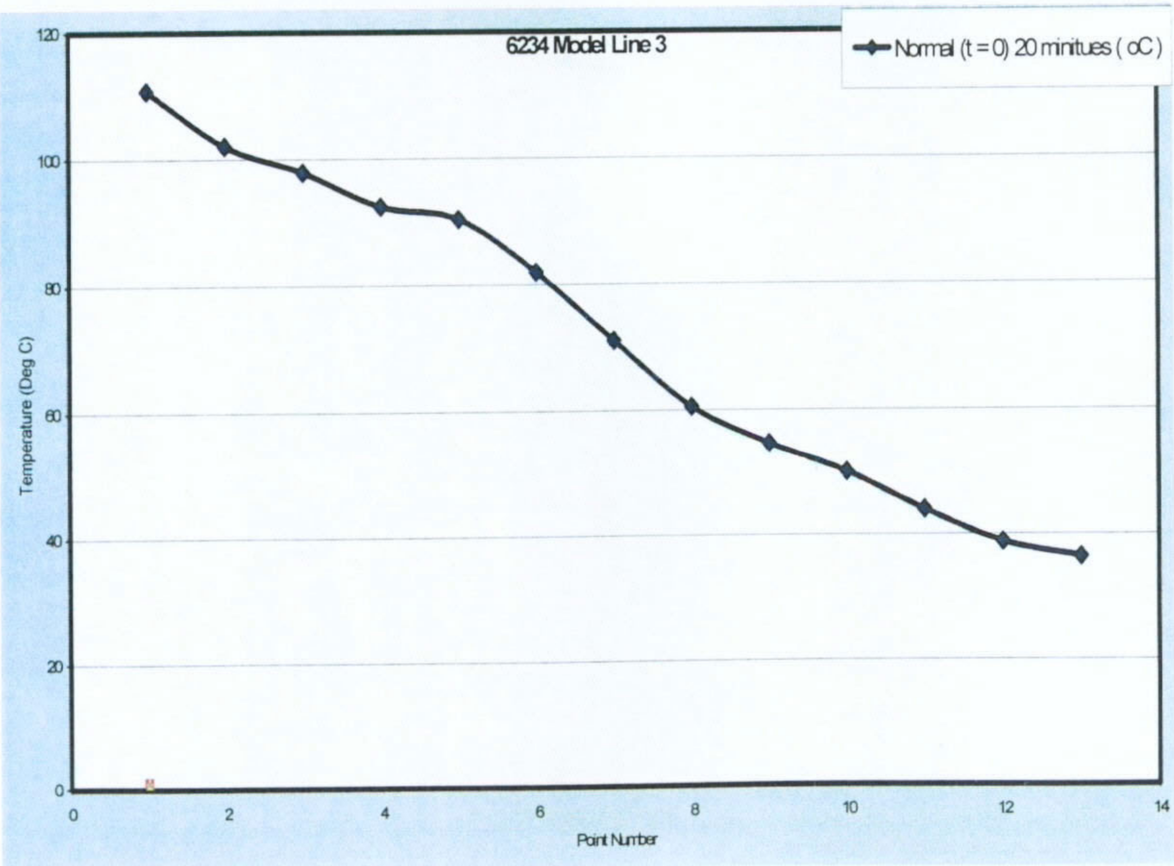


Fig. 145 Experimental Temperature Results of Model 6 (Line 3)

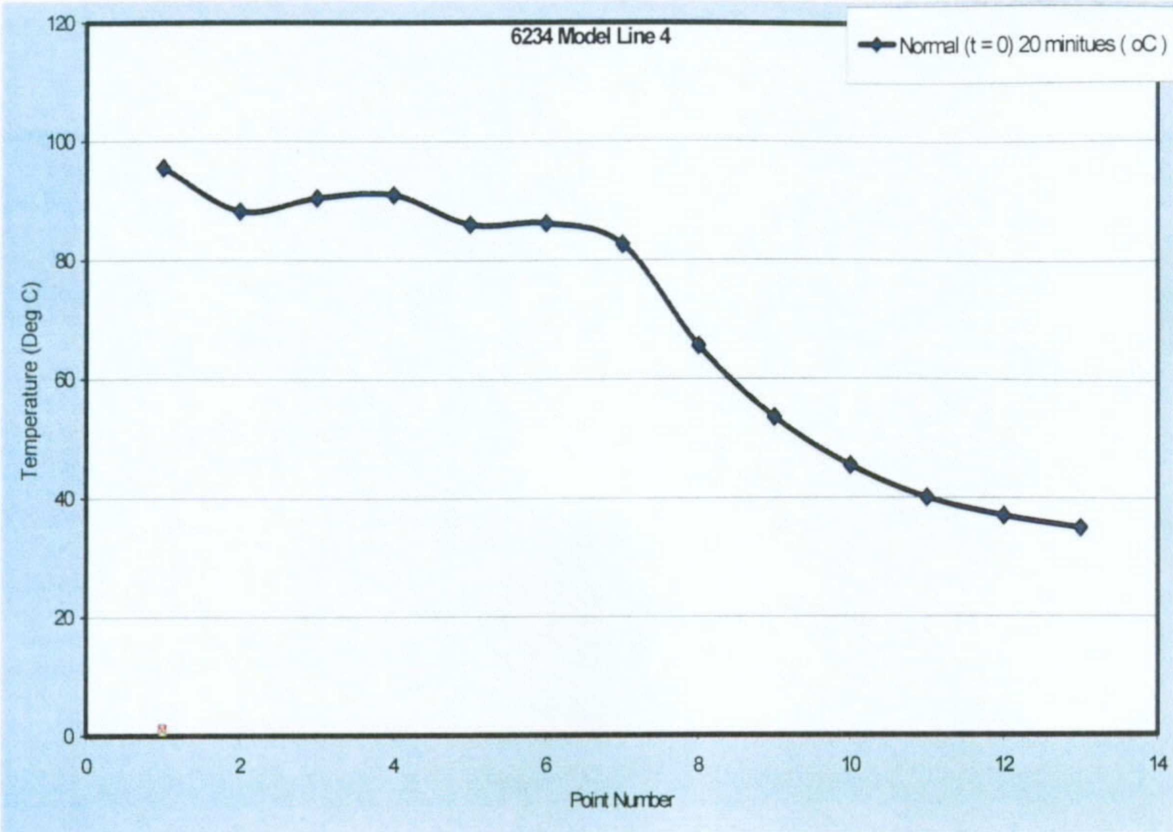


Fig. 146 Experimental Temperature Results of Model 6 (Line 4)

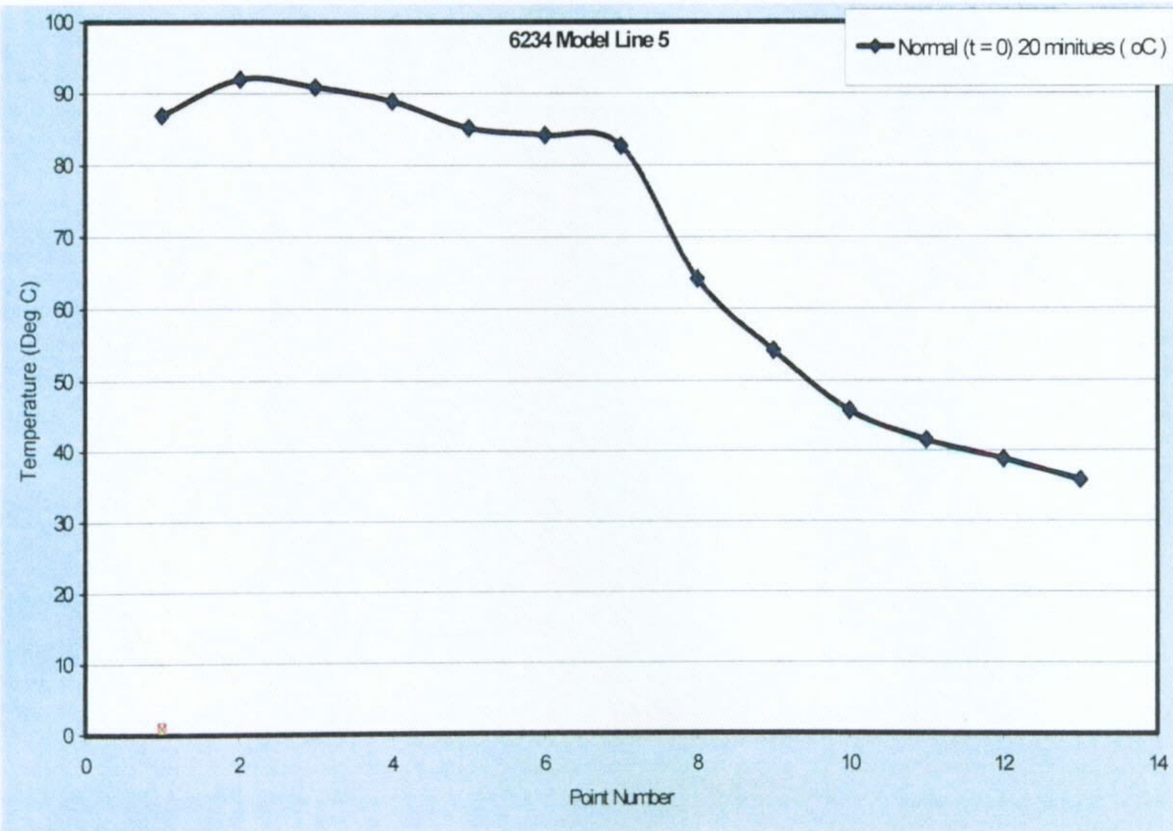


Fig. 147 Experimental Temperature Results of Model 6 (Line 5)

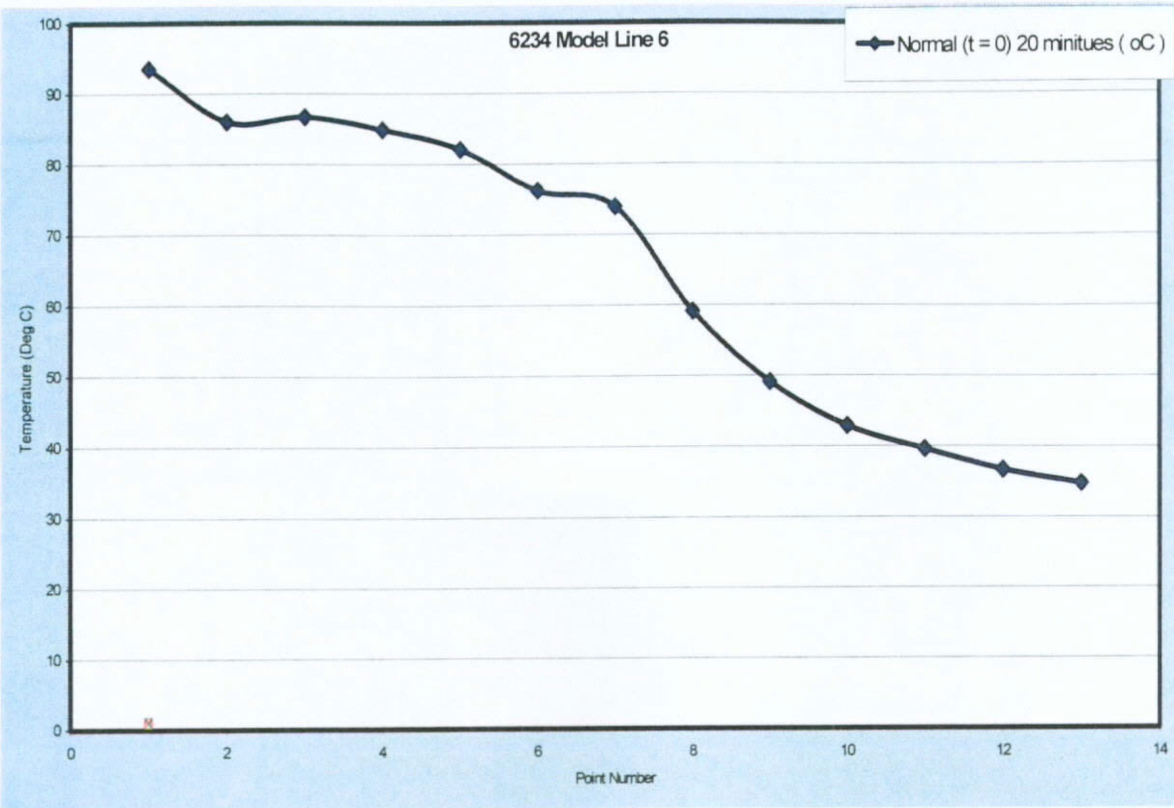


Fig. 148 Experimental Temperature Results of Model 6 (Line 6)

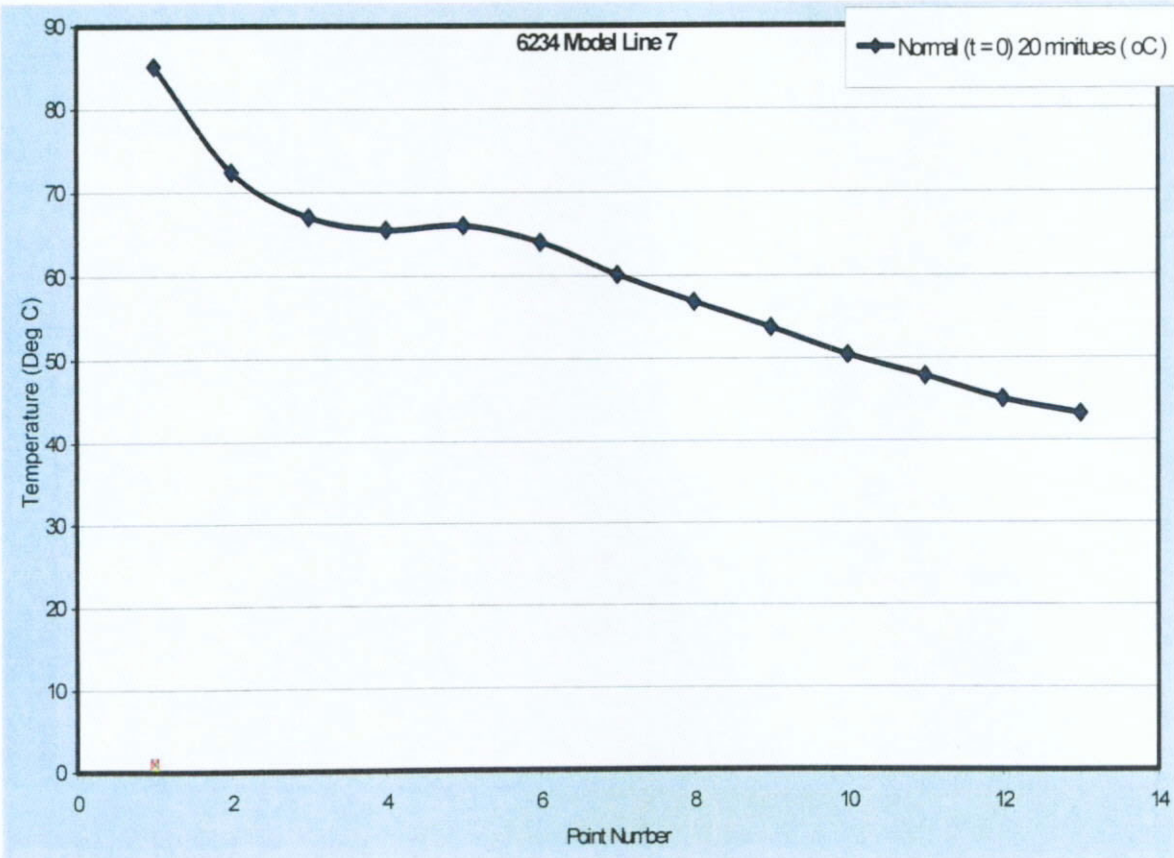


Fig. 149 Experimental Temperature Results of Model 6 (Line 7)

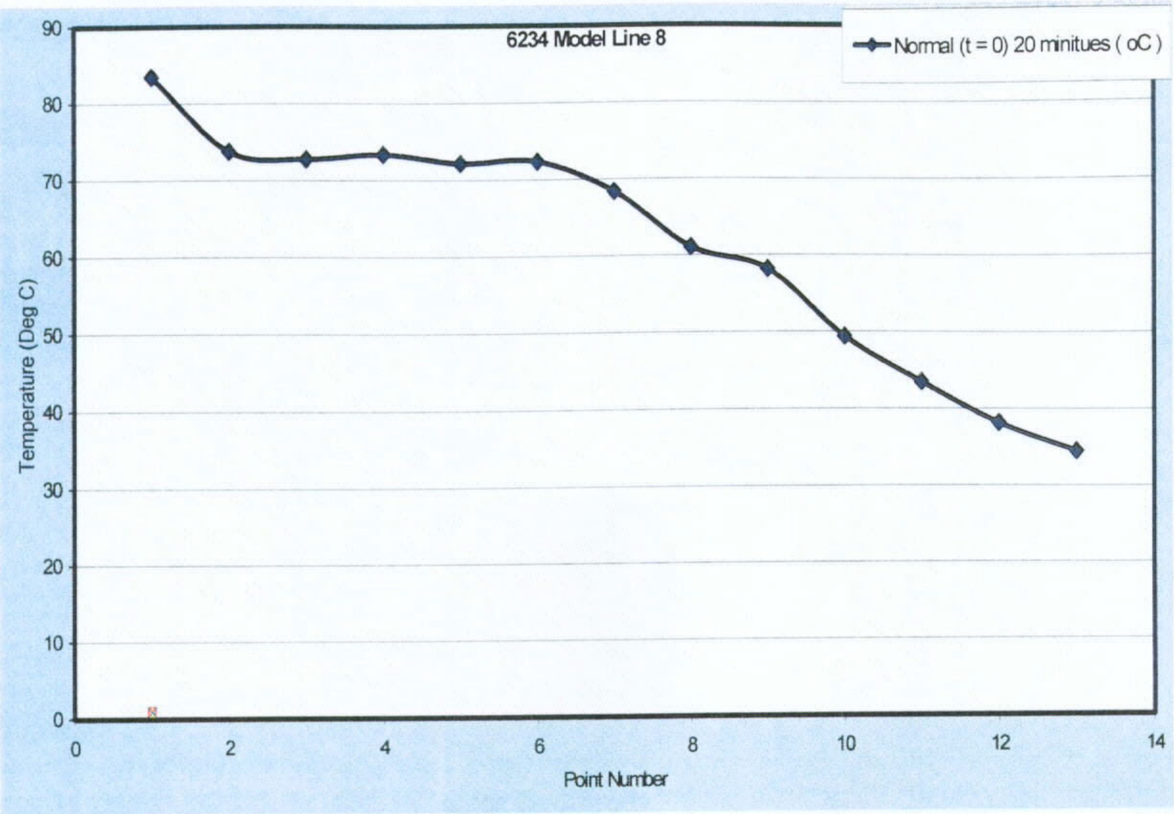


Fig. 150 Experimental Temperature Results of Model 6 (Line 8)

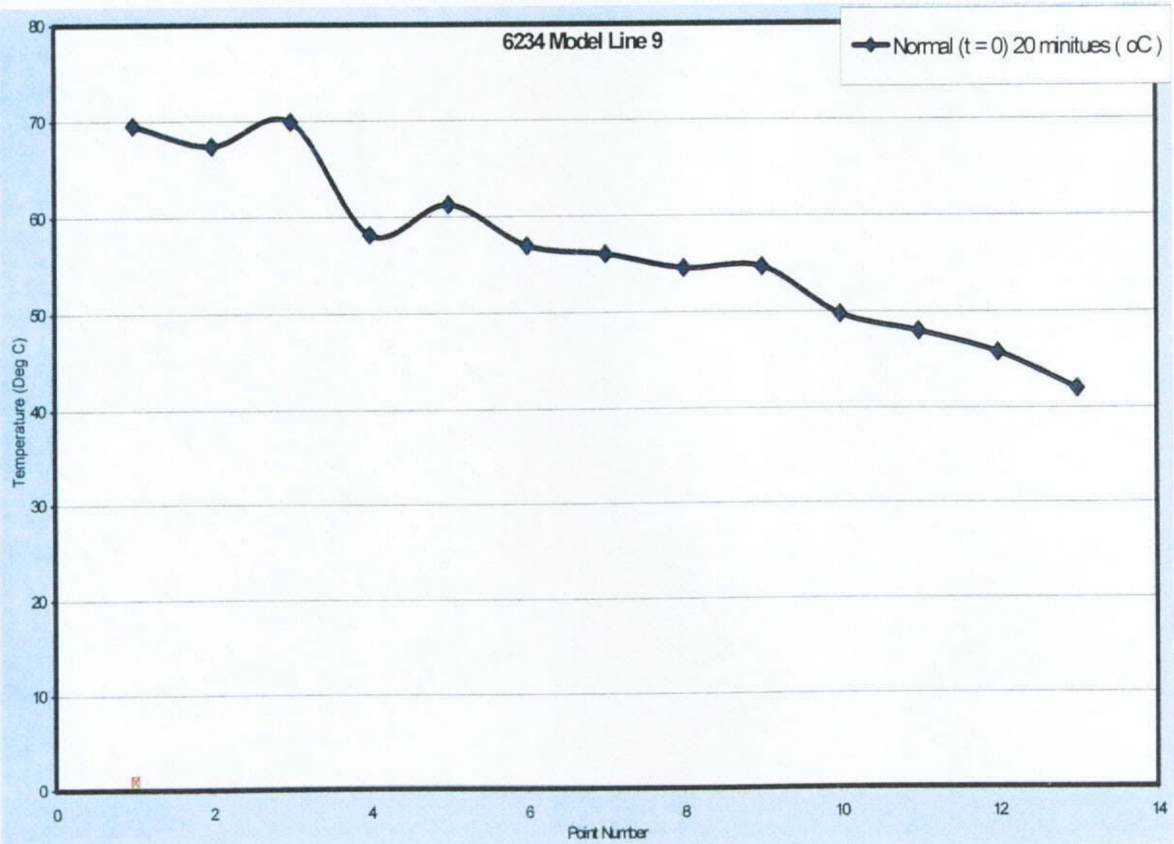


Fig. 151 Experimental Temperature Results of Model 6 (Line 9)

Appendix V – The KIC System Configuration

Hardware

- PC with Pentium 4 CPU or above
- 512 MB memory or above
- 360MB free hard disk space (60MB – system and software installation, 300 MB – swapping space)
- Network card and modern
- CD-ROM drive

Software

- Window 2000/ XP (1G Disk space Required)
- Web Browser – Netscape Navigator version 6.0 or higher (47MB disk space required)
- Pro/Engineer 2001 and Pro/Mechanica with Pro/Weblink (1.5 G disk space)
- Microsoft excel (250MB disk space)
- Statistica neural network (100 Mb disk space)

Appendix VI - List of the Published Papers

Two conference papers were produced and the second paper is now accepted to publishing to KIC-5 Book - "Knowledge Intensive Design Tools"

Paper 1

Title of the paper: Use of Knowledge Intensive CAD in Small Electrical Household Appliance Industry

Name of the conference: Annals of Int'l CORP Design Seminar, 19-18 May 2002 in Hong Kong

Paper 2

Title of the paper: Use of Knowledge Intensive CAD (KIC) in Virtual Product Validation

*Name of the conference:*Knowledge Intensive Computer Aided Design-V, IFIP WG 5.2 Knowledge Intensive CAD Workshop, Malta 2002

Organizer: The University of Malta