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A KNOWLEDGE-BASED PERFORMANCE MEASUREMENT SYSTEM FOR PRODUCTION PLANNING AND MACHINE SELECTION

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M. Phil

The Hong Kong Polytechnic University

2010
A Knowledge-based Performance Measurement System
for Production Planning and Machine Selection

LAM Chau Yi Annie

A thesis submitted in partial fulfilment of the requirements for
the degree of Master of Philosophy

July 2009
Certificate of Originality

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LAM Chau Yi Annie (Name of student)
Abstract

In today’s dynamic and competitive environment, there is intense pressure for manufacturing companies to face external and internal changes and uncertainties, including demand fluctuations, variations in customer requirements, decreases in product life cycles, and machine breakdowns. To react to these unpredictable changes, manufacturing companies must maintain a higher flexibility in their manufacturing system through the effective use of production assets. This, however, cannot be done without physical asset management (PAM), which plays an increasingly important role in achieving maximum lifetime effectiveness, utilization and return from physical assets, such as production machines, shop floors, and operating equipment. In the last decade, majority of researchers viewed PAM only from the maintenance perspective; they suggested various strategies and fault diagnosis tools to schedule maintenance activities and monitor machine health condition so as to reduce machine interruption. Although machine breakdowns are reduced after the provision of maintenance, it still does not guarantee that the machine can function effectively during its lifetime. To reflect the effective use of machine and increase its flexibility, it is necessary that the performance of physical asset operations be measured and evaluated.

On the other hand, because unpredictable changes, such as customer requirements and machine breakdowns, often occur in the actual production shop floor, companies should promptly make complex decisions on manufacturing planning, including machine selection, process flow planning, production scheduling, and resource allocation. Often, such decisions rely on production supervisors’ knowledge and experience. Thus, the design of a knowledge-based performance measurement approach is formulated to support performance evaluation of the utility
of physical assets, as well as the process of decision making pertaining to manufacture planning.

This thesis proposes a knowledge-based performance measurement system (KPMS) to support the decision-making processes of production planning and machine selection. The front-end module of KPMS uses data collection technologies such as radio frequency identification (RFID) and sensors to capture real-time manufacturing data from shop floors. The core module of KPMS involves a knowledge-based engine based on artificial intelligence (AI) techniques to derive useful knowledge from manufacturing operations data and performance indicators for decision support on production planning and resource allocation. In addition, a machine flexibility assessment function is included in the core module of KPMS to support the decision on machine selection. To validate the feasibility of using KPMS in providing reliable decision support for manufacturers in production planning and machine flexibility assessment, an industrial application case study was conducted in a helmet manufacturing company. The study found that with KPMS, the efficiency and reliability of manufacturing operations greatly improved and the firm’s flexibility in dealing with changes was enhanced significantly.
Publications Arising from the Thesis

(2 international journals papers have been published. 1 conference paper has been published.)

List of International Journal Paper


List of Conference Paper

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I would like to thank all the staff of YeeFung Polyfoam Limited for providing the field data and information for this research. Appreciation likewise goes to my colleagues in the RFID team, Miss Meina Cheng, Mr. Ocean Ng, Mr. Burly Tan, Mr. Gabriel Lee, Mr. Jacky Ting, Mr. Ivan Cheung, and Miss Elsa Chan for their help and support.

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**Table of Contents**

**Abstract**  
**Publications Arising from the Thesis**  
**Acknowledgements**  
**Table of Contents**  
**List of Figures**  
**List of Tables**  
**List of Abbreviations**

<table>
<thead>
<tr>
<th>Chapter 1  Introduction</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 Background of the Study</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Statement of the Problem</td>
<td>4</td>
</tr>
<tr>
<td>1.3 Research Objectives</td>
<td>7</td>
</tr>
<tr>
<td>1.4 Thesis Outline</td>
<td>8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 2  Literature Review</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 Introduction</td>
<td>10</td>
</tr>
<tr>
<td>2.2 Physical Asset Management</td>
<td>10</td>
</tr>
<tr>
<td>2.2.1 Importance of Physical Asset Management in the Manufacturing Industry</td>
<td>10</td>
</tr>
<tr>
<td>2.2.2 Background of Physical Asset Management</td>
<td>13</td>
</tr>
<tr>
<td>2.2.3 Recent Research on Physical Asset Management</td>
<td>15</td>
</tr>
<tr>
<td>2.2.4 Implications between Physical Asset Management and Performance Measurement</td>
<td>17</td>
</tr>
<tr>
<td>2.3 Performance Measurement</td>
<td>19</td>
</tr>
<tr>
<td>2.3.1 Overview of Performance Measurement</td>
<td>19</td>
</tr>
<tr>
<td>2.3.2 Performance Measurement Frameworks and Models</td>
<td>21</td>
</tr>
<tr>
<td>2.3.3 Performance Measures and Performance Measurement Methodologies</td>
<td>25</td>
</tr>
<tr>
<td>2.3.4 Importance of Manufacturing Flexibility</td>
<td>28</td>
</tr>
<tr>
<td>2.4 Performance Measurement System (PMS) and Knowledge-based System (KBS) Development</td>
<td>30</td>
</tr>
<tr>
<td>2.4.1 Overview of Current PMS</td>
<td>30</td>
</tr>
<tr>
<td>2.4.2 Knowledge-based System (KBS) Development in PMS</td>
<td>32</td>
</tr>
<tr>
<td>Section</td>
<td>Title</td>
</tr>
<tr>
<td>---------</td>
<td>-------</td>
</tr>
<tr>
<td>2.4.3</td>
<td>Technologies Adoption of KBS Development</td>
</tr>
<tr>
<td>2.4.4</td>
<td>RFID and Sensor Technologies in the Manufacturing Industry</td>
</tr>
<tr>
<td>2.5</td>
<td>Summary of the Literature Review</td>
</tr>
</tbody>
</table>

**Chapter 3**  
**The Knowledge-based Performance Measurement System (KPMS)**

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Introduction</td>
<td>48</td>
</tr>
<tr>
<td>3.2</td>
<td>KPMS System Architecture</td>
<td>49</td>
</tr>
<tr>
<td>3.3</td>
<td>Radio Frequency-based Manufacturing Data Collection Module (RFMC)</td>
<td>50</td>
</tr>
<tr>
<td>3.3.1</td>
<td>RFID Technology for Real-time Manufacturing Data Collection</td>
<td>51</td>
</tr>
<tr>
<td>3.3.2</td>
<td>Sensor Technology for Real-time Manufacturing Data Collection</td>
<td>64</td>
</tr>
<tr>
<td>3.3.3</td>
<td>Data Warehouse for Management of Manufacturing Data</td>
<td>66</td>
</tr>
<tr>
<td>3.4</td>
<td>Knowledge-based Performance Measurement Module (K-PM)</td>
<td>69</td>
</tr>
<tr>
<td>3.4.1</td>
<td>Knowledge-based Engine</td>
<td>70</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Machine Flexibility Assessor</td>
<td>79</td>
</tr>
<tr>
<td>3.5</td>
<td>Summary</td>
<td>81</td>
</tr>
</tbody>
</table>

**Chapter 4**  
**System Implementation and Case Study**

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>Introduction</td>
<td>83</td>
</tr>
<tr>
<td>4.2</td>
<td>Case Study in a Manufacturing Company (YeeFung Polyfoam Limited)</td>
<td>83</td>
</tr>
<tr>
<td>4.3</td>
<td>Problem Definition of YeeFung Polyfoam Limited</td>
<td>85</td>
</tr>
<tr>
<td>4.4</td>
<td>KPMS Implementation in YeeFung Polyfoam Limited</td>
<td>85</td>
</tr>
<tr>
<td>4.4.1</td>
<td>The RFID System’s Physical Setup on the Production Shop Floor</td>
<td>86</td>
</tr>
<tr>
<td>4.4.2</td>
<td>Sensor Installation for Data Capture</td>
<td>95</td>
</tr>
<tr>
<td>4.4.3</td>
<td>The Data Manipulation Framework in the Data Warehouse</td>
<td>98</td>
</tr>
<tr>
<td>4.4.4</td>
<td>Determine KPIs’ Content to Support Knowledge Creation</td>
<td>99</td>
</tr>
<tr>
<td>4.5</td>
<td>KPMS’ Operations Mechanism in the Decision Support for Production Planning</td>
<td>102</td>
</tr>
<tr>
<td>4.6</td>
<td>KPMS’ Operations Mechanism in the Decision Support for Machine Flexibility Assessment</td>
<td>109</td>
</tr>
</tbody>
</table>
### Chapter 5  Results and Discussion  115

5.1  Introduction  115
5.2  Comparison of the Conventional Approach and the Proposed System  115
5.3  Results of KPMS Implementation in YeeFung Polyfoam Limited  119
5.4  Discussion of KPMS Contribution  123

### Chapter 6  Conclusion  126

6.1  Summary of Research Work  126
6.2  Contributions of the Research  127
6.3  Research Limitations  128
6.4  Suggestions for Future Work  130

### References  132
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1.1</td>
<td>Physical Asset Management Philosophy for Manufacturing Companies</td>
<td>2</td>
</tr>
<tr>
<td>Figure 2.1</td>
<td>Phases of Developing a Performance Measurement System (from Bourne et al., 2000)</td>
<td>23</td>
</tr>
<tr>
<td>Figure 2.2</td>
<td>RBR Process (from Pal and Palmer, 2000)</td>
<td>38</td>
</tr>
<tr>
<td>Figure 3.1</td>
<td>The Generic Architecture of KPMS</td>
<td>50</td>
</tr>
<tr>
<td>Figure 3.2</td>
<td>Architecture of an RFID System</td>
<td>51</td>
</tr>
<tr>
<td>Figure 3.3</td>
<td>Steps of RFID System Deployment</td>
<td>55</td>
</tr>
<tr>
<td>Figure 3.4</td>
<td>Technical Sensors for Data Capture (Adapted from Hauptmann (1993))</td>
<td>65</td>
</tr>
<tr>
<td>Figure 3.5</td>
<td>Types of Sensor Systems: (a) Sensor System with Discrete Construction; (b) Sensor System with Integrated Sensor; (c) Intelligent Sensor (Extracted from Hauptmann (1993))</td>
<td>65</td>
</tr>
<tr>
<td>Figure 3.6</td>
<td>Steps in Data Management and Storage in Data Warehouse</td>
<td>67</td>
</tr>
<tr>
<td>Figure 3.7</td>
<td>The Hierarchical Structure of Performance Indicators Selection</td>
<td>71</td>
</tr>
<tr>
<td>Figure 3.8</td>
<td>A CBR Cycle (Extracted from Kolondner, 1993)</td>
<td>76</td>
</tr>
<tr>
<td>Figure 4.1</td>
<td>Sports Helmets Manufactured by YeeFung Polyfoam Limited</td>
<td>84</td>
</tr>
<tr>
<td>Figure 4.2</td>
<td>Standard Manufacturing Process for Sports Helmets</td>
<td>84</td>
</tr>
<tr>
<td>Figure 4.3</td>
<td>Manufacturing Process Flow of Helmet Production</td>
<td>87</td>
</tr>
<tr>
<td>Figure 4.4</td>
<td>(a) The Staff Sticks the RFID Tag on a WIP Helmet (b) A RFID-tagged Helmet</td>
<td>87</td>
</tr>
<tr>
<td>Figure 4.5</td>
<td>(a) Setup of Orientation Test (b) Horizontal Orientation (c) Vertical Orientation</td>
<td>88</td>
</tr>
<tr>
<td>Figure 4.6</td>
<td>Results of Orientation Test</td>
<td>89</td>
</tr>
<tr>
<td>Figure 4.7</td>
<td>(a) WIP Helmets Placed in a Polystyrene Box (b) The Polystyrene Boxes With WIP Helmets Are Stacked on the Material Handling Equipment</td>
<td>89</td>
</tr>
</tbody>
</table>
### Figure 4.8 (a) Setup of Height Test (b) Tagged Helmet Was Put Inside the Polystyrene Box  90

### Figure 4.9 Results of Height Test  90

### Figure 4.10 (a) Snow Helmet (b) Road Helmet (c) High-end Road Helmet  91

### Figure 4.11 (a) Setup of Tag Performance Test (b) RFID-Tagged helmet  92

### Figure 4.12 Results of Tag Performance on Different Products  93

### Figure 4.13 The Proposed RFID Gateways Setup in YeeFung Polyfoam Limited  93

### Figure 4.14 Transfer of RFID-tagged WIP Helmets through RFID Gateway  94

### Figure 4.15 Data Collected by RFID Devices  94

### Figure 4.16 Reading Rate of Tagged WIP Helmets When Passing through RFID Gateway  95

### Figure 4.17 Sensors' Installation in an Injection Molding Machine  96

### Figure 4.18 Device Connected with Sensors For Data Capture  97

### Figure 4.19 Transfer of Data Captured by Sensors to Computer  97

### Figure 4.20 Integrating RFID and Sensor Data in the Measurement of Machine Efficiency for Processing a Product Item  99

### Figure 4.21 Average Hourly Throughput of a Machine in the Week of 5/8/2008  101

### Figure 4.22 Cycle Time of Injection Molding Machine Collected on 5/8/2008  101

### Figure 4.23 Throughput of a Machine at Different Working Hours  102

### Figure 4.24 The Workflow of KPMS  103

### Figure 4.25 User Input Interface of KPMS for YeeFung Polyfoam Limited  104

### Figure 4.26 The Retrieved Case Results of the KPMS  108

### Figure 4.27 The Workflow of KPMS  110

### Figure 5.1 Workflow of the Conventional Approach  116

### Figure 5.2 Workflow of the KPMS Approach  117
List of Tables

Table 2.1  Comparison between Traditional and Non-traditional Performance Measures (from Ghalayini et al., 1997)  21
Table 2.2  Performance Measurement Frameworks and Models Developed by Various Researchers  22
Table 2.3  Performance Measures for Measuring Manufacturing Performance  26
Table 3.1  Comparison Between Passive RFID System and Active RFID System  52
Table 3.2  Comparison of RFID Frequency Bands (Adapted from Kwok et al., 2007)  54
Table 3.3  The Attributes and Parameters for Case Representation  77
Table 4.1  The Test Results Generated by RFID-DO (1 represents the best performance and 0 represents the worst performance)  92
Table 4.2  The Operating Status of an Injection Molding Machine on 5/8/2008  98
Table 4.3  The KPI Measurement Formula  100
Table 4.4  Saaty’s 1–9 Scale for AHP Preference  105
Table 4.5  Each Category’s Level of Importance  105
Table 4.6  Corresponding Weighting Value of Each Category  105
Table 4.7  Comparison between the Input Case and Historical Case  107
Table 4.8  The Specifications of Injection Molding Machines for Producing AA002  111
Table 4.9  The Machine Flexibility among Five Injection Molding Machines  112
Table 4.10  The RMF from Machine 001 to Other Machines  113
Table 5.1  Comparison of Conventional Approach and KPMS Approach in Managing Production Activities  118
Table 5.2  The Measurement Areas of KPMS Implementation in YeeFung Polyfoam Limited  120
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AHP</td>
<td>Analytic Hierarchy Process</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>CBM</td>
<td>Condition-based Maintenance</td>
</tr>
<tr>
<td>CBR</td>
<td>Case-based Reasoning</td>
</tr>
<tr>
<td>CMMS</td>
<td>Computerized Maintenance Management System</td>
</tr>
<tr>
<td>DSS</td>
<td>Decision Support System</td>
</tr>
<tr>
<td>EPC</td>
<td>Electronic Product Code</td>
</tr>
<tr>
<td>ERP</td>
<td>Enterprise Resource Planning</td>
</tr>
<tr>
<td>EPP</td>
<td>Expandable Polyethylene</td>
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<tr>
<td>EPS</td>
<td>Expandable Polystyrene</td>
</tr>
<tr>
<td>ES</td>
<td>Expert System</td>
</tr>
<tr>
<td>HF</td>
<td>High Frequency</td>
</tr>
<tr>
<td>IT</td>
<td>Information Technology</td>
</tr>
<tr>
<td>IZA</td>
<td>Interrogation Zone Analysis</td>
</tr>
<tr>
<td>JIS</td>
<td>Just-In-Sequence</td>
</tr>
<tr>
<td>JIT</td>
<td>Just-In-Time</td>
</tr>
<tr>
<td>K-PM</td>
<td>Knowledge-based Performance Measurement module</td>
</tr>
<tr>
<td>KBS</td>
<td>Knowledge-based System</td>
</tr>
<tr>
<td>KPI</td>
<td>Key Performance Indicator</td>
</tr>
<tr>
<td>KPMS</td>
<td>Knowledge-based Performance Measurement System</td>
</tr>
<tr>
<td>LF</td>
<td>Low Frequency</td>
</tr>
<tr>
<td>MF</td>
<td>Machine Flexibility</td>
</tr>
<tr>
<td>MMIS</td>
<td>Maintenance Management Information System</td>
</tr>
<tr>
<td>MTO</td>
<td>Make-To-Order</td>
</tr>
<tr>
<td>OEE</td>
<td>Overall Equipment Effectiveness</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>OEM</td>
<td>Original Equipment Manufacturer</td>
</tr>
<tr>
<td>PAM</td>
<td>Physical Asset Management</td>
</tr>
<tr>
<td>PMQ</td>
<td>Performance Measurement Questionnaire</td>
</tr>
<tr>
<td>PMS</td>
<td>Performance Measurement System</td>
</tr>
<tr>
<td>RBR</td>
<td>Rule-based Reasoning</td>
</tr>
<tr>
<td>RCM</td>
<td>Reliability-Centered Maintenance</td>
</tr>
<tr>
<td>RF</td>
<td>Routing Flexibility</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>RFID-DO</td>
<td>Radio Frequency Identification-Deployment Optimizer</td>
</tr>
<tr>
<td>RFMC</td>
<td>Radio Frequency-based Manufacturing Data Collection Module</td>
</tr>
<tr>
<td>RMF</td>
<td>Relative Machine Flexibility</td>
</tr>
<tr>
<td>TPA</td>
<td>Tag Placement Analysis</td>
</tr>
<tr>
<td>TPM</td>
<td>Total Productive Maintenance</td>
</tr>
<tr>
<td>UHF</td>
<td>Ultra High Frequency</td>
</tr>
<tr>
<td>WIP</td>
<td>Work-In-Process</td>
</tr>
<tr>
<td>WORM</td>
<td>Write Once, Read Many</td>
</tr>
</tbody>
</table>
Chapter 1 Introduction

1.1 Background of the Study

In the last decade, manufacturing shifted from traditional mass production mode of creating scale efficiency to modern manufacturing modes such as make-to-order, mass customization, agile manufacturing, and lean manufacturing, which are adopted to meet customers’ orders at shorter time and lower cost. At present, manufacturing companies are challenged to provide efficient and cost-effective responses to the unpredictable changes in current customer-oriented manufacturing environment. These changes come from varying customer requirements, fluctuations in demand patterns, proliferation of niche markets, increase in product mix, decrease in product life cycles, and increasing competition between manufacturers (Sharifi and Zhang, 2001). To cope with these changes, manufacturing companies need to maintain a higher flexibility and responsiveness within their manufacturing systems and have better use of their production assets. Physical asset management (PAM) plays an increasingly important role in achieving maximum effectiveness, utility, and return from physical assets such as production machines, shop floors, and operating equipment. Therefore, manufacturing companies should plan and monitor their physical assets throughout their entire life cycle, from their development/procurement stage through operation to eventual disposal (Woodward, 1997).

As shown in Figure 1.1, manufacturing companies adopt a PAM philosophy to gain maximum lifetime effectiveness for their physical assets, hence increase their operational effectiveness and reduce operating cost under a dynamic manufacturing environment. In the life cycle of physical asset, the operation stage is said to be the longest and the most important because it is the productive, revenue-generating stage.
of asset lifetime (Mitchell, 2002). Thus, manufacturing companies should plan and monitor their physical asset during the operation stage in order to optimize their use.

![Physical Asset Management Philosophy for Manufacturing Companies](image)

Figure 1.1 Physical Asset Management Philosophy for Manufacturing Companies

In the operation stage of physical assets, the critical issues are the effective utilization and allocation of physical assets (such as machines) to job orders through production planning and monitoring exercises. In addition, companies should provide maintenance activities to physical assets to prevent these assets from failing and to maintain their production capacity. During the last decade, majority of researchers viewed PAM solely from the maintenance perspective; they suggested various
strategies and fault diagnosis tools to schedule maintenance activities and monitor machine health condition so as to reduce machine downtime. Examples of these studies include maintenance management information system (Kobbacy et al., 1995), computerized maintenance management system (Jonsson, 2000), e-maintenance system (Han and Yang, 2006) and Watchdog agent™ (Lee et al., 2006). However, reduced machine breakdowns after the provision of maintenance do not guarantee that the machine can be used effectively during its operation lifetime. Existing studies do not have enough consideration in planning and monitoring physical assets utilization and operation. Historical machine failure data is used to determine preventive maintenance schedules while sensors are adopted to track the health degradation of machine to predict failure. They are not intended to support performance measurement and planning of machine utilization. Thus, it is difficult to capture real-time data of physical assets utilization and operation for planning and monitoring. To reflect the effectiveness of physical asset utilization, production managers should adopt a performance measuring system to reveal the actual performance of manufacturing operations and identify the effect of resource utilization. The ultimate function of a performance measure is to evaluate the effectiveness of the activities within a manufacturing process, or the outputs of a process, in achieving a company’s specified goals.

Based on the review of related studies, cost, quality, time, and flexibility were frequently used as the core dimensions that measure manufacturing performance. Under the current dynamic market environment, flexibility is a critical performance measure in that it shows the efficiency of a manufacturing process in reacting to changes. Because the PAM perspective is highlighted in the manufacturing industry since it can enhance the lifetime effectiveness of physical assets, machine flexibility (MF) is the most important dimension to be considered. MF shows how easily a
particular machine can adapt to changes and uncertainties, such as machine breakdown, heavy load, implementing different sequences, or dispatching rules to reduce setup time. To enable accurate measurement of MF and physical asset operations, certain data collection and analysis technologies including radio frequency identification (RFID) and sensor should be adopted to capture the required data within the production process in a real-time manner. With real-time manufacturing data, it is important to develop a performance measurement system (PMS) that analyzes and transforms collected data into MF measures and other performance indicators, which become useful information and knowledge that support the decision over machine selection and production planning. Thus, this research aims to develop a knowledge-based performance measurement system (KPMS), with a combination of data collection technologies including RFID and sensor, performance measures, and artificial intelligence (AI), to help manufacturing companies improve their operational effectiveness by providing them with the right knowledge on resource allocation and planning and monitoring of the utilization of physical assets and their operation.

1.2 Statement of the Problem

To survive in the current competitive environment, manufacturing companies strive to produce customized products within short lead time and low manufacturing cost to fulfill customer orders. To produce a product, various production resources such as machines, equipment, shop floors, raw materials, and workers are required to coordinate through appropriate planning and scheduling. Since most manufacturing companies have automated their manufacturing processes by investing on production machines and equipment to increase the productivity, the effective utilization of these physical assets is critical to their overall success. Companies are aware of the
importance of PAM in helping them achieve the maximum lifetime effectiveness, utility, and return from the physical assets invested. Currently, the majority of studies on PAM initiatives have been found to focus on the maintenance perspective only. Such studies suggested various maintenance strategies and fault diagnosis tools to schedule maintenance activities and monitor machine condition so as to reduce machine downtime. However, apart from maintenance activities, resource allocation decisions in production planning would also have a significant effect on the utility of physical assets. Since a production shop floor usually contains a number of machines where production capabilities vary, assigning suitable job orders to each machine during production planning would enhance the operational effectiveness of machine utilization. Therefore, companies should consider machine utility and production planning of physical assets in PAM initiatives.

As seen from the literature review, a number of approaches and systems have been developed to suggest different maintenance approaches so as to prevent the machine failure. However, a systematic approach to measure the performance of physical asset operations and supporting production planning decisions is seldom addressed. Manufacturing companies encounter four major problems:

(i) **Lack of data on physical asset operations**

Normally, manufacturing companies use enterprise resource planning (ERP) systems to record the data and information of manufacturing orders. However, ERP systems provide only manufacturing data related to customer information, purchasing details, product information, order requirements, and production details. ERP cannot provide the data on physical asset operations such as machine status and location of work-in-process (WIP) goods. Therefore, manufacturing companies lack the data which reflect physical asset operations performance for evaluation purposes.
(ii) Production planning dependent on staff experience

Since manufacturing companies need to fulfill various customer orders with different production requirements, then they should have production planning before actual production. Production planning involves making complex decisions on manufacturing process flow, machine selection, resource allocation, production scheduling, and setting performance indicators. Currently, these production planning decisions often rely on the knowledge and experience of production supervisors. Given limited resource and machine capability, production planning decisions must be made carefully especially with regard to utilizing the resource/machine fully while keeping the productivity level steady without breakdown. As the product life cycle is shortened in the current market, manufacturing companies have to handle an increasing amount of customer orders within a short lead time, hence further increasing the challenge of formulating a production plan. A knowledge-based system, which provides knowledge in supporting production planning decisions, is deemed necessary to help companies formulate production plans for different customers.

(iii) Difficulty in measuring the performance of manufacturing operations

To measure the performance of manufacturing operations comprehensively, various manufacturing data such as order information, product details, production statuses, and quality inspection, are required. However, these manufacturing data are spread in different production shop floors and departments. Moreover, the data stored in the ERP system used by manufacturers are transaction-based; therefore, these data do not provide any performance reporting function. Since there is a lack of platform to integrate various manufacturing data from different sources, manufacturers will find it quite difficult to review the performance of manufacturing operations.
(iv) Lack of flexibility measure to deal with uncertainties

Because the manufacturing environment is dynamic, changes and uncertainties (machine breakdown included), late delivery of incoming materials, and urgent production orders are often experienced. To deal with these uncertainties, production supervisors should promptly decide on shifting job orders in between different machines. However, production supervisors often make decisions based on their own experience and personal judgment. They do not have any flexibility measure to provide them with objective data of machine capabilities for making the decisions.

1.3 Research Objectives

This research has the following specific objectives:

(i) To establish a system infrastructure related to data collection technologies to capture data of physical assets operations from production shop floors, hence provide a foundation for the measurement of operational performance of a company’s physical assets.

(ii) To create a performance measurement system platform for managing and integrating manufacturing data from different production shop floors and departments and transforming them into meaningful performance indicators.

(iii) To develop a knowledge-based system using artificial intelligence technologies to manipulate production knowledge for production supervisors to make the right decisions during production planning.

(iv) To design a machine flexibility measure approach that enables production staff to consider the capability of each machine in real time so as to facilitate the reassignment of job scheduling from one machine to another during the event of production uncertainties.
1.4 Thesis Outline

This thesis consists of six chapters described as follows:

(i) Chapter 1 (Introduction) describes the background to the study, followed by the research problems that occur in supporting performance measurement of physical asset operations and production planning decisions in the manufacturing industry. Chapter 1 also states the research objectives.

(ii) Chapter 2 is a literature review, which studies the importance of physical asset management in the manufacturing industry. The review also states the implications of both physical asset management and performance measurement. Chapter 2 also reviews the frameworks, models, and the methodologies of performance measurement. Finally, the analysis of performance measurement systems and the development of knowledge-based systems and enabling technologies are also discussed.

(iii) Chapter 3 introduces the system architecture of the proposed knowledge-based performance measurement system (KPMS). After that, the detailed mechanism of the two modules of KPMS, including Radio Frequency-based Manufacturing Data Collection Module (RFMC) and Knowledge-based Performance Measurement Module (K-PM) is described.

(iv) Chapter 4 provides an industrial case study of the implementation of KPMS. To validate the feasibility of adopting KPMS in providing reliable knowledge-based decision support for manufacturers in production planning and machine flexibility assessment, a KPMS prototype is developed and operated in a company manufacturing helmets. The chapter also illustrates the operations mechanism of KPMS in decision support.

(v) Chapter 5 presents the results and discussion of the proposed system after implementation. A workflow study of the conventional approach and the
proposed system is compared. The results and contributions of implementing
KPMS in a manufacturing company are discussed.

(vi) Chapter 6 provides the conclusion that summarizes the research work. The
contributions made by this research are also identified. Finally, some
limitations of the research and suggestions for future work are presented.
Chapter 2 Literature Review

2.1 Introduction

This thesis is focused on the design of a knowledge-based performance measurement system to help address the problems associated with manufacturing planning and machine selection. The literature review is presented in three important sections: the background study of physical asset management; the performance measurement and current methodologies; and the development of a knowledge-based performance measurement system. A research summary appears in the last section of this chapter. This literature review seeks to identify published studies on the application of knowledge-based system and technology development on performance measurement.

A review of the available research is presented in this chapter. Section 2.2 discusses the background study of physical asset management in the manufacturing industry. Section 2.3 identifies performance measurement, its frameworks, models and methodologies development. Section 2.4 analyzes knowledge-based system and relevant technology development into performance measurement. Section 2.5 summarizes this chapter.

2.2 Physical Asset Management

2.2.1 Importance of physical asset management in the manufacturing industry

According to Anosike and Zhang (2007), one of the major problems facing manufacturing organizations is how to respond rapidly and cost-effectively to the unpredictable changes that take place in today’s global market. These changes result from continuous variations in customer requirements, fluctuations in demand patterns, proliferation of niche markets, continuous increases in product mix,
decreased product life cycles, and increasing competition among manufacturers (Sharifi and Zhang, 2001). According to Hormozi (1994), customer satisfaction has become more difficult to achieve and manufacturing enterprises have to be agile and responsive to market changes so they can maintain their competitive position in the market. The concept of agile manufacturing has been developed to help manufacturing enterprises achieve positions that can potentially meet global demand (Kidd, 1994; Kidd, 1996). According to Goldman et al. (1994), agile manufacturing means that the production process must be able to respond quickly to the changes in information from the market. This requires compressing lead time in terms of information flow, material flow, and material ability, in short notices, to change to a wide variety of products (Kidd, 1995). Naylor et al. (1999) stated that agile manufacturing requires a high level of rapid reconfiguration and will eliminate as much waste as possible, but does not emphasize the elimination of all wastes as a prerequisite. The strategy for agile manufacturing must enable manufacturing systems to be more flexible, responsive, and re-configurable to highly variable demand patterns and product mixes, shorter design, and manufacturing lead times as well as better utilization of resources (Dhumal et al., 1996).

Apart from maintaining agile and flexible manufacturing systems, lean manufacturing is another initiative that many major businesses in the United States have been trying to adopt to remain competitive in an increasingly global market. Accordingly, the focus of the approach is on cost reduction by eliminating non-value-added activities (Abdulmalek and Rajgopal, 2007). According to Hayes and Pisano (1994), lean manufacturing uses less, or the minimum, of everything required to produce a product or perform a service. Leanness calls for the elimination of all wastes or in lean terminology “muda”, and achieves this by eliminating all non-value-adding processes (Womack et al., 1990). Lean manufacturing, by its very
nature, tends to reduce demand variation by simplifying, optimizing, and streamlining the supply chain (Naim, 1997). Harrison (1995) declared that lean manufacturing avoids the requirement for robustness by making demand stable through the use of market knowledge and information, and forward planning. Current manufacturing practices usually focus on two main areas:

(a) Maintaining an agile and flexible manufacturing system to respond quickly to changes in demand and product mixes and to reduce the design and manufacturing lead times.

(b) Adopting a lean manufacturing system to reduce the cost by eliminating all waste and non-value-added activities.

However, the greatest challenge facing operating and production enterprises is the need to maintain, and often increase, operational effectiveness, revenue, and customer satisfaction, while simultaneously reducing capital, and operating and support costs (Mitchell, 2002). Hence, the need to ensure effective utilization of production assets has become an even greater requirement for the overall success of a business. Maximizing revenues requires that marketable products should be supplied at the lowest possible long-term cost, thus there is a need for optimum utilization of capacity (Bleazard and Khu, 2001). Physical assets form the basic infrastructure of all businesses and effectively managing these assets is essential to the success of such businesses. Accordingly, Woodward (1997) asserts that planning and monitoring the assets throughout from the development/procurement stage through to eventual disposal is essential. In addition, Schuman and Brent (2005) argue that the effective management of a company’s physical assets plays an increasingly important role in optimizing business profitability.
2.2.2 Background of Physical Asset Management

Hipkin (2001) stated that physical asset management (PAM) includes engineering activities, as well as the adoption of a variety of approaches to maintenance such as reliability-centered maintenance, multi-skilling, total productive maintenance, and hazard and operability studies. PAM has been defined as a strategic, integrated set of comprehensive processes (which include financial, management, engineering, and operating and maintenance) for the physical assets to have maximum lifetime effectiveness, utility, and return from physical assets such as production and operating equipment and structures (Mitchell and Carlson, 2001). In Schneider et al.’s (2006) study, PAM is defined as operating a group of assets over the whole technical lifecycle, guaranteeing a suitable return and ensuring defined service and security standards. Bleazard and Khu (2001) proposed that the overall goal of PAM philosophy is a long-term productivity optimization. This process can unlock hidden production capacity, mitigate failure consequences, and improve profitability dramatically.

Furthermore, PAM is frequently used synonymously with maintenance management, although the former encompasses a broader range of activities and applications. PAM not only incorporates the traditional maintenance sphere of activities but also includes buildings and structures, many of which have no relationship with production activities (Hipkin, 1998). To sustain the manufacturing productivity and customer satisfaction at the highest possible level, maintenance strategies have been widely used to decrease downtime, needless repair work, while increasing both quality and productivity (Han and Yang, 2006). According to Pintelon and Gelders (1992), maintenance of industrial manufacturing equipment can be defined as all activities necessary to restore equipment to, or keep it in, a specified operating condition. They believe that the objective of maintenance is to maximize
equipment availability in an operating condition, hence permitting the desired output quantity and quality. In addition, maintenance must be realized in a cost-effective way and must conform to safety and environmental regulations. The purpose of maintenance has generally been perceived as the prevention of failures to attain adequate availability and reliability (Banerjee and Flynn, 1987; Bennett and Jenney, 1980).

According to Han and Yang (2006), maintenance is a complex process that consists of object selection, sensor installation, data acquisition, data transformation, data analysis, decision making, maintenance operation planning, reporting to operators, management of stocks, and others. The importance of the maintenance function has increased because of its role in keeping and improving availability, product quality, safety requirements, and plant cost-effectiveness levels because maintenance costs constitute an important part of the operating budget of manufacturing companies (Al-Najjar and Alsyouf, 2003). Depending on the specific industry, maintenance costs can represent from 15% to 40% of the cost of goods produced; a third of this amount is spent on unnecessary or improperly performed maintenance activities (Mobley, 1990). Furthermore, Moore and Starr (2006) mentioned that inadequate maintenance can result in higher levels of unplanned asset failure, which has many inherent costs to the company, including lost production, rework, scrap, labor, spare parts, fines for late orders, and lost orders because of unsatisfied customers. These costs are associated with maintenance labor and materials, and are likely to go even higher in the future with the addition of factory automation through the development of new technologies (Han and Yang, 2006). As management of physical assets now accounts for a rapidly increasing share of operational costs, greater attention is being directed to maintenance thinking (Hipkin and De Cock, 2000). According to Bleazard and Khu (2001), establishing effective,
long-term physical assets practices and procedures has a profound impact on the profitability of any business venture. A PAM strategy can dramatically improve profitability by unlocking hidden production capacity and mitigating failure consequences.

2.2.3 Recent Research on Physical Asset Management

Eti et al. (2006) suggested that today’s competitive environment requires industries to succeed in sustaining full production capabilities, while minimizing capital investment. From the maintenance perspective, this means maximizing equipment reliability by achieving maximum uptime, while extending the plant’s life. This proactive approach needs a total planned quality maintenance program, the systemizing of all (i.e., preventive, predictive, and planned) maintenance, plus the control of maintenance quality. Equipment reliability and maintenance drastically affect three key elements of competitiveness: quality, cost, and production lead time. Well-maintained machines hold tolerances better, reduce scrap and rework, and raise consistency and quality of the parts. In addition, such machines increase uptime and yield of good parts, thereby cutting total production costs and shortening lead times by reducing downtime and the need for retooling (National Research Council, 1990).

BP Amoco, one of the biggest energy companies in the world, uses a multi-enterprise asset management system which was developed by Maximo to create business process capabilities in all areas of physical asset management, including asset operations, maintenance, materials management, purchasing, product sourcing, supplier contract management, and to provide management information for each of these sets of activities (Holland et al., 2005). Moreover, some companies have used preventive and predictive maintenance approaches either by using historical maintenance data or by sensing machine condition to avoid machine
downtime (Lee, 1996). A computerized maintenance management system (CMMS)
is a platform that collects and records data for maintenance control and
manufacturing process improvement, and supports the integration of functions and
speeds up the flow of proper information (Jonsson, 2000). According to Kobbacy et
al. (1995), most maintenance management information systems (MMIS) can track
components, provide logistics support, store maintenance history, alarm
predetermined maintenance activities, and produce management reports. It was
reported that CMMS realizes better labor productivity and equipment availability,
better availability of technical data and maintenance history information, and easier
performance reporting (Mann, 1983). By sensing machine condition, Lee et al.,
(2006) suggested intelligent prognostics tools that can continuously track health
degradation and extrapolate temporal behavior of health indicators to predict risks of
unacceptable behavior over time as well as pinpoint exactly which component of the
machine is likely to fail. Said tools can monitor the degradation rather than detect the
faults in a networked environment and ultimately optimize asset utilization in the
facility.

In 2006, Han and Yang (2006) developed a new e-maintenance system that is
dependent upon coordination, cooperation, and negotiation through the use of the
Internet and tether-free (i.e., wireless, web, etc.) communication technologies. Said
system enables manufacturing operations to achieve near-zero-downtime
performance on a sharable, quick, and convenient platform by integrating existing
advanced technologies with distributed sources. Apparently, e-maintenance benefits
a distributed organization, which means the plant, people, expertise or data are
physically separated or isolated (Moore and Starr, 2006). However, since many
manufacturers have their headquarters and factories at different geographic locations
because of the effects of globalization, the practice of PAM is thus becoming more
2.2.4 Implications between Physical Asset Management and Performance Measurement

The above reviews show that companies can exploit PAM strategy to achieve the greatest lifetime effectiveness and utility of their physical assets so as to optimize productivity and improve profitability. Currently, majority of researchers view PAM solely from the maintenance perspective, emphasizing on adopting different maintenance strategies such as preventive maintenance, reliability-centered maintenance (RCM), condition-based maintenance (CBM), and total productive maintenance (TPM) to prevent failure or significant damage on the production equipment, which can maintain the required production capacity and reduce machine downtime and maintenance costs. Fault diagnoses and intelligent prognostics tools such as knowledge-based infotronics supervisory system (Wang et al., 2006), Watchdog Agent™ (Lee et al., 2006), and smart asset maintenance system (Leung and Tse, 2007) are proposed to sense equipment condition, monitor its degradation process and suggest maintenance activities. Some computerized systems (such as CMMS and MMIS) are mainly used to collect and record data related to maintenance activities and control. However, apart from maintenance issues, the scope of PAM should be extended to other areas such as asset operations, performance evaluation, materials management, purchasing, and risk analysis. For instance, Özbayrak and Bell (2003) proposed a knowledge-based decision support system to manage the parts and tools in flexible manufacturing systems. Said system consists of three knowledge-based models to schedule production jobs, select the best tool issue strategy, and diagnose and remedy tooling-originated manufacturing problems. Moreover, Schuman and Brent (2005) developed an asset life cycle management
(ALCM) model, which guides decisions made during the early stages of a project in the process industry to increase the long-term performance of assets at reduced life cycle costs. By adopting PAM strategies in companies, machine failure rate and maintenance costs are expected to be reduced because of better preventive maintenance practices. On the other hand, the performance of physical assets can be evaluated, monitored, and enhanced to allocate resources properly while optimizing the effectiveness and utility of assets.

PAM can help companies to improve their performance by utilizing and managing their physical assets properly and cost-effectively. To achieve this goal, companies should obtain the critical information of the performance of physical assets under different applications to support the resources allocation decision. PAM is no longer confined to maintenance issues only; its scope should be extended to include measuring and evaluating the asset operations and performance by collecting asset data in real time. Based on key performance indicators, companies can evaluate the performance of physical assets in performing different job orders. This helps them to optimize asset utility and allocate assets to the suitable job tasks by considering their actual performance.

On the other hand, in the age of digital information, owing to the rise of e-commerce and information technology, a large amount of data has been automatically or semi-automatically collected in modern industry (Chien et al., 2007). Companies are faced with the problem that most of the collected data tend to be archived rather than used because of the complexity of data extraction and presentation (Dabbas and Chen, 2001). It is a challenging task to transform this massive data into meaningful information that is easy to access, interpret, and manipulate. Furthermore, decision makers usually have the difficulty to diagnose many malfunctions efficiently, which arise at machine, cell, and entire system levels.
during manufacturing operations (Özbayrak and Bell, 2003). Most engineers rely on their own domain knowledge and experience to identify the specific characteristics of abnormal products, although such judgments are ineffective and limited by their own domain knowledge (Chien et al., 2007). As a result, the dynamic manufacturing environment increases the complexity of measuring the performance of physical assets in different operations. To address this issue, a performance measurement system is necessary so that the performance of physical assets is evaluated and measurement is transformed into some kinds of performance indicators. A performance measurement system helps companies to extract meaningful information and useful knowledge from massive asset operational data. Eventually, with a performance measurement system, companies can monitor and improve the asset performance and make better decisions on resource allocation by optimizing asset utility.

2.3 Performance Measurement

2.3.1 Overview of Performance Measurement

Performance measurement is defined as a process of quantifying the efficiency and effectiveness of actions that lead to performance (Neely et al., 1995). The essential function of a performance measure is to assess how well the activities within a process, or the outputs of a process, achieve specified goals. This involves a comparison of actual operation results with predetermined goals and an assessment of the extent of any deviation from those goals. A target level of performance is usually expressed as a quantitative standard, value, or rate (Ahmad et al., 2005). To monitor performance and goal realization, manufacturing performance areas should be measured in the form of key performance indicators (KPI) based on internal or external data collected during operations. According to Chan and Chan (2004), KPI
can be measured objectively and subjectively. Objective measures use mathematical formulas to calculate the respective values, while the subjective measures use stakeholders’ opinions and personal judgment. Nudurupati et al. (2007) suggested that implementing KPI not only improves business performance but also changes the culture of people from intuitive to fact-based decision making. It can be seen that performance measurement in business monitors performance, identifies the areas that need attention, enhances motivation, improves communication, and strengthens accountability (Waggoner et al., 1999).

Performance measurement revolution started in the late 1970s and early 1980s with the dissatisfaction of traditional backward-looking accounting-based performance measurement systems (Nudurupati and Bititci, 2005). At that time, the evaluation of performance was predominantly based on financial indicators. Examples of traditional performance measures developed from traditional accounting systems including profit, return on investment, return on assets, sales per employee, and productivity. However, the limitations of traditional performance measurement systems have been widely documented. Many authors recognize that traditional financial accounting systems can only indicate the performance that results from the activities of a company, but it is difficult to indicate how that performance is achieved or how it can be improved. Moreover, traditional financial performance measures have been criticized for being historical in nature (Dixon et al., 1990), encouraging minimization of variance rather than continuous improvement (Johnson and Kaplan, 1987; Lynch and Cross, 1991), being lagging indicators (Ghalayini et al., 1997; Nudurupati et al., 2007), being internally rather than externally focused, having little regard for competitors or customers (Kaplan and Norton, 1992; Neely et al., 1995), and encouraging short-termism that provides little indication of future performance (Hayes and Abernathy, 1980; Kaplan, 1986). To overcome these
limitations, a number of performance measurement frameworks and tools were developed for designing more balanced performance measures to provide an overall view of company performance. Table 2.1 summarizes the difference between traditional and non-traditional performance measures in terms of several criteria.

Table 2.1 Comparison between Traditional and Non-traditional Performance Measures (from Ghalayini et al., 1997)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Traditional performance measures</th>
<th>Non-traditional performance measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basis of system</td>
<td>Accounting standards</td>
<td>Company strategy</td>
</tr>
<tr>
<td>Types of measures</td>
<td>Financial</td>
<td>Operational and financial</td>
</tr>
<tr>
<td>Audience</td>
<td>Middle and top managers</td>
<td>All employees</td>
</tr>
<tr>
<td>Frequency</td>
<td>Lagging (weekly or monthly)</td>
<td>Real-time (hourly or daily)</td>
</tr>
<tr>
<td>Linkage with “reality”</td>
<td>Indirect, misleading</td>
<td>Simple, accurate, direct</td>
</tr>
<tr>
<td>Shop floor relevance</td>
<td>Ignored</td>
<td>Used</td>
</tr>
<tr>
<td>Format</td>
<td>Fixed</td>
<td>Flexible/variable</td>
</tr>
<tr>
<td>Local–global relevance</td>
<td>Static, non-varying</td>
<td>Dynamic, situation structure dependent</td>
</tr>
<tr>
<td>Stability</td>
<td>Static, non-changing</td>
<td>Dynamic, situation timing dependent</td>
</tr>
<tr>
<td>Purpose</td>
<td>Monitoring</td>
<td>Improvement</td>
</tr>
<tr>
<td>Support for new</td>
<td>Hard to adapt</td>
<td>Applicable</td>
</tr>
<tr>
<td>improvement approaches</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effect on continuous</td>
<td>Impedes</td>
<td>Supports</td>
</tr>
<tr>
<td>improvement</td>
<td></td>
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</tbody>
</table>

2.3.2 Performance Measurement Frameworks and Models

Based on the literature review, one can find many frameworks of performance measurement, which provide various non-traditional performance measures. Table 2.2 shows the performance measurement frameworks and models developed by various researchers. Among the performance measurement frameworks, balanced
scorecard (Kaplan and Norton, 1992) is widely accepted; it integrates four important performance perspectives: financial, customer, internal processes, and learning and growth. Balanced scorecard was developed to complement measures of past performance with measures of the drivers of future performance. The objectives and measures of the scorecard are derived from an organization’s vision and strategy (Kaplan and Norton, 1996).

Table 2.2 Performance Measurement Frameworks and Models Developed by Various Researchers

<table>
<thead>
<tr>
<th>Frameworks and tools</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balanced scorecard</td>
<td>Kaplan and Norton (1992)</td>
</tr>
<tr>
<td>Strategic measurement analysis and reporting technique (SMART) system</td>
<td>Cross and Lynch, (1988–1989)</td>
</tr>
<tr>
<td>Performance measurement questionnaire (PMQ)</td>
<td>Dixon et al. (1990)</td>
</tr>
<tr>
<td>Quantitative models for performance measurement systems (QMPMS)</td>
<td>Suwignjo et al. (2000)</td>
</tr>
<tr>
<td>Performance measurement matrix</td>
<td>Keegan et al. (1989)</td>
</tr>
<tr>
<td>Performance prism</td>
<td>Neely and Adams (2001)</td>
</tr>
<tr>
<td>Results and determinants framework</td>
<td>Fitzgerald et al. (1991)</td>
</tr>
<tr>
<td>European business excellence model</td>
<td>EFQM (1998)</td>
</tr>
</tbody>
</table>

Another system, the strategic measurement analysis and reporting technique (SMART), consists of a four-level pyramid of objectives and measures, which integrate performance through the hierarchy of the organization (Cross and Lynch, 1988–1989). The performance measurement questionnaire (PMQ) developed by Dixon et al. (1990) helps to identify strengths and failings in the current performance measurement system; a workshop is then proposed to develop, revise, and re-focus the set of performance measures. Suwignjo et al. (2000) developed the quantitative models for performance measurement systems (QMPMS) to identify factors affecting performance and their relationships, structure them hierarchically, and
quantify the effect of factors on the performance by using cognitive maps, cause-and-effect diagrams, tree diagrams, and the analytical hierarchy process. These frameworks are multidimensional and focus more on non-financial, external, and future-looking performance measures to redress the balance (Bourne et al., 2000). Moreover, performance measures are believed to have been derived from a company's strategy (Kaplan and Norton, 1996).

As shown in Figure 2.1, Bourne et al. (2000) developed a theoretical framework to describe the development of performance measurement systems in three phases: (i) design of performance measures, (ii) implementation of performance measures, and (iii) use of performance measures.

(i) The design phase of performance measure

The design phase of performance measure is subdivided into two requirements: identifying key objectives to be measured and designing the measures.

![Figure 2.1 Phases of Developing a Performance Measurement System (from Bourne et al., 2000)](image)
(ii) Implementation phase of performance measure

In this phase, systems and procedures are put in place to collect and process the data, thus measurements are made regularly. This may involve computer programming to trap data from the existing system and present them in a more meaningful form or initiate new procedures to capture information that is currently not recorded.

(iii) Use phase of performance measure

In this phase, the two main functions are: assessing the implementation of strategy and challenging the strategic assumptions of strategy.

It has been noted that the three phases can overlap as different individual measures are implemented at different rates. However, most of the literature has concentrated on the conceptual frameworks and models for designing the performance measures, which is an early stage of developing performance measurement systems. Little research attention has been placed on the development stages after the design of performance measures such as implementation and use of performance measurement systems.

On the other hand, many researchers have emphasized the importance of reviewing and managing the evolution of performance measurement system as situation changes. According to Ghalayini and Noble (1996), a performance measurement system should include an effective mechanism for reviewing and revising targets and standards. Moreover, it should include a process for developing individual measures to deal with changes in performance and circumstances (Maskell, 1989; Dixon et al., 1990; McMann and Nanni, 1994) and periodically reviewing and revising the complete set of measures to coincide with the changes in competitive environment and strategic direction (Wisner and Fawcett, 1991; Dixon et al., 1990;
Lingle and Schiemann, 1996). Given the availability and effective use of performance measurement systems, Kennerley and Neely (2003) proposed three subsequent phases for effective evolution of the systems. These are: (i) reflection on the existing system to identify any inappropriate areas and needs for enhancements, (ii) modification of the system to ensure alignment with the organization’s new circumstances, and (iii) deployment of the modified system to manage the performance of the organization.

2.3.3 Performance Measures and Performance Measurement Methodologies

As revealed in the previous sections, a number of researchers recognized the need to use various non-traditional performance measures rather than traditional financial indicators in their performance measurement frameworks and models. Subsequently, new dimensions of performance measures such as quality, time, flexibility, and delivery are adopted in measuring manufacturing performance. According to Jose et al. (1999), the first international manufacturing strategy survey, which was carried out in 20 international countries, found that companies use a variety of indicators to measure their company and market performance. Table 2.3 summarizes the performance measures that various researchers used to measure manufacturing performance. The table shows that the performance measures that were frequently used were cost, quality, time, flexibility, and delivery.

When selecting performance measures appropriate to a particular company, the company should consider its strategic intentions, which are formed to suit the nature of business and the competitive environment in which it operates (Ahmad and Dhafr, 2002). In addition, the company should balance the range of performance measures to make sure that one dimension or set of dimensions of performance is not stressed to the detriment of others. According to Saaty (1980), decision makers are strongly
recommended to approximate the importance of each indicator by using analytic hierarchy process (AHP) and pair-wise comparisons. AHP has been widely applied in evaluating performance of manufacturing system (Yurdakul, 2002; Lee et al., 1995; Rangone, 1996). AHP can be used to quantify the relationship of each factor with the others with respect to overall performance (Bititci et al., 2001).

Table 2.3 Performance Measures for Measuring Manufacturing Performance

<table>
<thead>
<tr>
<th>Performance Measures</th>
<th>Authors</th>
<th>Cost</th>
<th>Time</th>
<th>Quality</th>
<th>Flexibility</th>
<th>Delivery</th>
<th>Dependability</th>
<th>Customer complaint</th>
<th>Equipment effectiveness</th>
<th>Safety and environment</th>
<th>Innovation</th>
<th>Productivity</th>
<th>Inventory</th>
<th>Efficiency</th>
<th>Reliability</th>
<th>Customer satisfaction</th>
<th>Diversity of product line</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yurdakul (2002)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td></td>
<td>Bititci et al. (2001)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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On the other hand, there are various methodologies for measuring manufacturing performance, including questionnaire, self-assessment against international standards and awards, KPI assessment, and interview.

a) Questionnaire

Vic and Maria (2001) introduced the use of a questionnaire to assess manufacturing performance. Ghalayini et al. (1997) applied questionnaire (Dixon et al., 1990) to develop the organization’s strategies, supporting areas of success, and associated performance measures. However, most assessment measures in the questionnaire are qualitative and are difficult to use to get any quantitative performance measure.

b) Self-assessment against international standards and awards

Self-assessment against various international standards and quality/business excellence awards is commonly used by organizations to measure and assess company performance through exercises of management reviews, internal and external audits (Chin et al., 2003). Examples of renowned awards are the Malcolm Baldrige National Quality Award (MBNQA), the European Quality Award (EQA), and the Deming Prize (DP). The objective of self-assessment is to help organizations identify their strengths, weaknesses, and opportunities for improvement (Karapetrovic and Willborn, 2001).

c) KPI assessment

Another methodology to assess performance quantitatively is KPI assessment (Ahmad and Benson, 1999). In this methodology, performance indicators that show important aspects of manufacturing performance areas and are usually fairly easy to measure or estimate are selected. In addition, supporting formulas are involved in generating data from the practice and assessing an accurate performance. The relevant performance indicators are compared with internal goals/standards,
competitors and customer demand to assess the relative performance of the company and identify performance gaps (Ahmad and Dhafr, 2002).

d) **Interview**

Manufacturing performance can be assessed by conducting interviews with customers and employees. For example, Nudurupati et al. (2007) conducted customer interviews to determine customers’ perception of the level of service they have received to improve their service to meet the desired customer needs. De Toni et al. (1997) examined the performance through cross-functional and multilevel meetings, in which top managers, production managers, and workers were involved in the judging of performances. Wen et al. (2007) used a group assessment method, which involved middle or top managers to award scores of each dimension for measuring enterprise performance. The managers gave the scores and corresponding weights based upon their own experiences and all the scores in the group assessment were summed and averaged to reduce subjective judgment on performance measurement.

### 2.3.4 Importance of Manufacturing Flexibility

According to Leong et al. (1990), the key dimensions of manufacturing performance can be defined in terms of quality, delivery speed, price (cost), and flexibility. Among these measurement factors, Gerwin (1987) observed that very little is known about the implications of flexibility for manufacturing management; he suggested that “part of the problem arises from the lack of operational measures of flexibility”. Cox (1989) sees the concept of flexibility as a measure of the efficiency, with which the manufacturing process can be changed. Cox focused on the issues of product mix and volume flexibility. In addition, various flexibility taxonomies have been developed to represent the flexibility measure in manufacturing systems. For instance, Sarker et al. (1994) reviewed flexibility in
manufacturing systems and proved that machine flexibility (MF) and routing flexibility (RF) are two of the most fundamental and important types of flexibilities.

**Machine flexibility (MF).** Brill and Mandelbaum (1989) defined MF as the set of all operations in a reference set that a machine can perform with a positive degree of efficiency. According to Wahab and Stoyan (2008), MF indicates how easily a particular machine can adapt to changes and uncertainties, such as machine breakdowns, heavy load, and different sequence or dispatching rules to reduce setup time. Therefore, by clearly defining MF in a manufacturing system, the enterprise is aided in the production of a product if another machine breakdown or certain product demand suddenly becomes large. In measuring MF, a number of technological attributes and performance indicators have been proposed. These include the time taken to set up (Chandra and Tombak, 1992), the efficiency of processing an operation (Brill and Mandelbaum, 1989; Das and Nagendra, 1993; Chen and Chung, 1996; Wahab, 2005), and the number and variety of operations a machine can perform (Sarker et al., 1994; Koste and Malhotra, 1999).

**Routing flexibility (RF).** Bernado and Mohamed (1992) defined RF as a system’s ability to continue producing a given part mix despite disturbances. Stecke and Raman (1995) defined RF as the measure of the alternative paths that a part can effectively follow through a system for a given process plan. Given that a manufacturing system has a high RF level, in case of machine breakdown, repair or maintenance, the production of a particular product can be re-routed more easily to other machines with no penalty to production (Wahab and Stoyan, 2008). Chang (2007) considers three attributes of RF measurement: (i) routing efficiency, (ii) routing versatility, and (iii) routing variety. Routing versatility is defined as a measure of efficiencies, whereas routing variety is a function of the difference
between routes, that is, the ratio of the number of different machines to the total number of machines. Therefore, when measuring RF in a manufacturing system, the efficiency of machine and material handling equipment must be considered because these two kinds of machines characterize a route in a manufacturing system.

Based on the above discussion about MF and RF, one can note that technological attributes are performance indicators of different resources and activities in a manufacturing system. Resources refer to machines, operators, robots, tools, buffers, material handling equipment, etc., and activities are the processing of products on machines, the transportation of products among workstations, or loading/unloading the parts from/to machines by the operators. To enable accurate measurement of MF, the implementation of performance measurement systems (PMSs) should be incorporated with data collection and analysis technologies that can measure the above technological attributes.

### 2.4 Performance Measurement System and Knowledge-based System Development

#### 2.4.1 Overview of Current PMS

Performance measurement system (PMS) consists of three interrelated elements: (i) individual measures that quantify the efficiency and effectiveness of actions, (ii) a set of measures that combine to assess the overall performance of a company, (iii) a supporting infrastructure that enables data to be acquired, collated, sorted, analyzed, interpreted, and disseminated (Neely, 1998). To ensure that actions are aligned to strategies and objectives, an appropriate PMS should be implemented and relevant measures should be maintained to continuously reflect the issues important to the company (Lynch and Cross, 1991). It was demonstrated that companies managed using integrated balanced PMS outperform those not managed by measures (Lingle
To measure the overall performance of a company, various performance measurement systems have been exploited. For instance, Ghalayini et al. (1997) developed an integrated dynamic performance measurement system (IDPMS), which integrates management, process improvement team, and factory shop floor in a company. The IDPMS helps managers identify the interactions among the general areas of success and their associated performance measures and indicators by synthesizing three existing tools: performance measurement questionnaire, half-life concept, and modified value-focused cycle time (VFCT) diagram. The IDPMS overcomes the limitations of existing performance measurement systems by allowing dynamic updating of its general areas of success, performance measures, and standards, and by encouraging continuous improvement. De Toni et al. (1997) presented the integrated production performance measurement system (IP2MS), which uses data from the manufacturing planning and control system (MPCS) and the activity-based costing system, to obtain production performance levels and reallocate a company’s productive resources based on the difference between actual and desired performance levels. According to Bititci et al. (2002), a web-enabled performance measurement system was implemented in a manufacturing site to collect numerical data from different sources such as MRPII system, spreadsheet, and database applications, and convert them into graphical Shewhart charts, which are presented on the web. Moreover, Nudurupati and Bititci (2005) studied the implementation and impact of information technology (IT)-supported performance measurement systems in three companies, in which IT support could be provided by an IT platform built from available tools such as MS Excel, MS Access, and web development tools, or an IT software purchased from the market such as enterprise resource planning (ERP) and business intelligence solutions.
2.4.2 Knowledge-based System (KBS) Development in PMS

Decision support systems are computer-based tools that aid the managerial decision-making process by presenting various effective alternatives. In the 1990s, knowledge-based intelligent systems played an important role as decision support tools (Chan, et al., 2000; Özbayrak and Bell, 2003). The ability of such systems in processing knowledge led to cost savings, faster decision process, good payoff, and significant competitive advantage (King, 1990; Bonarini and Maniezzo, 1991; Finlay, 1992; Guida et al., 1992 and Meyer et al., 1992). With the increase and maturation of information technology, and the growing popularity of the Internet, these techniques provide companies an opportunity to enhance the techniques applied in knowledge-based expert systems and decision support systems to help managers tackle the quickly changing business markets (Koutsoukis et al., 1999; Liang and Huang, 2000; Liao, 2002).

Because of the significance of performance measurement, KBS is often used to support decision making in this aspect. KBS possesses wide potential applicability in decision making in respect of measuring performance. In the 1980s, Bowen and Paying (1987) described an expert system prototype which analyses performance indicators. These are key statistics describing levels of achievement in terms of both policy objectives and efficiency. Fisher and Nof (1987) proposed a KBS to aid analysis in the appraisal of manufacturing facilities. Matsatsinis et al. (1997) developed a multiple-criteria knowledge-based decision support system (MCKBEDSS) to evaluate business performance and financial ability. Cil and Evren (1998) suggested a framework for the acquisition of new manufacturing technology that links manufacturing strategy, market requirements, and manufacturing attributes using an expert system approach. In addition, some more recent and good examples of using KBS in manufacturing performance measurement are shown as follows.
Cheung et al. (2003) proposed a multiperspective knowledge-based system for customer service management, which incorporates case-based reasoning and adaptive time-series model for decision analysis, performance measurement, and monitoring. Humphreys et al. (2003) developed a knowledge-based system, which integrates environmental criteria into the supplier selection process and provides guidelines for purchasing managers to evaluate the environmental management performance of the suppliers. In 2007, Wen et al. constructed a knowledge-based decision support system (KDSS) for measuring enterprise performance; it provides decision makers with various financial data, evaluation of enterprise performance based on knowledge reasoning and prediction of future total sales by artificial neural network, so that they can understand current and future financial situations and make decisions faster. Wang et al. (2008) designed an intelligent decision support system for performance evaluation (DSSPE) to analyze the productive efficiency of state-owned enterprises in a developing country by using data envelopment analysis (DEA) models. Wang et al. (2007) developed a novel model via the extraction of fuzzy-business rules from databases for obtaining resource-allocation knowledge as well as allocating resources efficiently. The proposed model uses a genetic algorithm to find the best priority sequence of customer orders for resource allocation and, in accordance with the priority sequence of orders, a fuzzy-inference model to allocate the resources and to determine the order completion time.

From the above review of related studies, it is found that artificial intelligence (AI), data management, and mining techniques are promising technologies to develop an expert system and KBS for modern manufacturing enterprises to support different aspects of performance measurement. Since profits gained from such investments are promising, many modern manufacturing enterprises have begun to deal with knowledge engineering to develop an intelligent system for strengthening
their productivity and competitiveness (Wang et al., 2007). The next section highlights the technology adoption for the development of KBS in this research.

2.4.3 Technology Adoption of KBS Development

Generally, KBS has the following basic components: a knowledge base, an inference engine, and a specific user interface (Dhaliwal and Benbassat, 1996). Knowledge base contains domain knowledge useful for problem solving. To use experiences effectively, knowledge extraction and collection must be continually performed; moreover, the data must be stored in the knowledge base in the form of rules or cases, which enable the inference engine to infer and generate suggestions or actions quickly and accurately (Wen et al., 2005). Additionally, to automate and retain the knowledge of an enterprise, KBS is designed to facilitate knowledge acquisition, sharing, and diffusion (Davenport and Prusak, 1998; Preece et al., 2001). Thus, such systems can explain to their users both the knowledge the systems contain and the reasoning processes that are gone through.

(i) Case-based Reasoning (CBR) in KBS Development

Case-based reasoning (CBR) is one of the AI technologies widely used in knowledge capturing and representation. CBR is a recent approach to problem solving and learning; it has received much research interest over the last decades (Aamodt and Plaza, 1994; Kolodner, 1993; Sinoudis, 1992). Founded on the psychological theory of human reasoning, CBR recognizes that humans often solve a new problem by comparing it with similar ones they had resolved in the past (Chua et al., 2001). Knowledge-based intelligent systems, including CBR, play an increasingly important role in today’s industrial applications (Yen et al., 1995; Mezgar et al., 2000; Lee et al., 2004). A review of literature shows that intelligent
systems such as CBR could benefit domain users in that it provides consistency in decision making, improves learning capability, supports knowledge reuse and retention, and yields instantaneous decision support.

CBR simulates the human problem-processing model and can have the self-learning function by constant accumulation of past experience (Tseng et al., 2005). CBR is a problem-solving methodology that relies on past, similar cases to find solutions to problems, to modify and criticize existing solutions and explain anomalous situations (Kolodner, 1991). The main idea of CBR is to adapt solutions that were used to solve old problems and use them to solve new problems (or cases). In this way, CBR can help to solve the problem by retrieving similar previous cases (Kolodner, 1993). CBR helps decision makers reuse all their past problem-solving experiences to deal with a new case.

Intervening mechanism is mainly used to derive a solution from stored cases. When a new case is presented to the system, CBR will follow a cycle consisting of four processes (Aamodt and Plaza, 1994): retrieving the most similar case(s); reusing the case(s) to attempt to solve the problem; revising the proposed solution if necessary; and retaining the solution as part of a new case.

The CBR cycle starts by retrieving similar past cases from the case library based on a similarity measure. It then matches indexes of the new case with those of past cases and computes a similarity value, which indicates how closely the new case resembles each past case. After the evaluation, only past cases with highest similarity are retrieved. The solutions of the retrieved similar past cases are reused to infer a proper solution to solve the current problem. As there may be differences between the most similar case and the new case, the suggested solution needs to be revised to fit the new problem. Once the solution is confirmed, the new case is retained in the case library to achieve the self-learning function and knowledge regeneration for
In general, a CBR system consists of two components: a case library and an inference mechanism (Pal and Palmer, 2000).

(a) The case library, which acts as a source of knowledge, is a repository of previous cases that store information regarding a specific problem and its corresponding solution. Each case in the library is composed of three parts, namely, case number, case indexes, and solution sets (Cheung et al., 2003). The structure of a case can be represented as: Case (case number, case indexes, solution sets). Case number is assigned by the system sequentially to each case to provide a unique designation. Case indexes are the identities of the cases that describe the problem situation and are entered into the case library to ensure that they can be accurately retrieved. The solution sets include the solutions of previous cases that can be reused and adapted to solve a new case.

(b) In the inference mechanism, the retrieval methods of CBR can be broadly classified into two types: inductive-based and nearest neighbor-based methods (Aha et al., 1991). Inductive-based retrieval method determines the features that can discriminate cases in the best way and generates a decision tree-type structure to organize the cases in the memory. The nearest neighbor-based retrieval method applies an exhaustive search method to evaluate the dissimilarity between all past cases and the new case. Similar past cases are then selected by comparing the dissimilarity evaluations. Because of its implementation simplicity and error toleration, the nearest neighbor-based retrieval method has been commonly used in CBR systems (Watson, 1997). However, its limitation is that it would incur high computation costs when a large number of past cases are evaluated (Tsai et al., 2005).
(ii) Rule-based Reasoning (RBR) in KBS Development

In Rule-based Reasoning (RBR) in KBS development, specialized domain knowledge is represented as a set of IF <precondition(s)> THEN <conclusion(s)> rule format. It is often extremely difficult to obtain an appropriate set of rules in an application domain to cover all possible eventualities (Pal and Palmer, 2000). If the antecedent clauses are true, then the consequent clauses are true. In general, a RBR system consists of two components: rule repository and inference mechanism.

(a) Rule repository. In a rule-based system, knowledge is represented as facts about the world, that is, relationships between entities, for example, A → B and mechanisms (known as inference engine) for manipulating the fact. One might construct a network of rules that are interconnected to form a repository of knowledge, known as rule base. Therefore, the rule in the rule base is triggered if its antecedent matches. Knowledge engineers elicit knowledge rules based on professional expert’s experiences (e.g., operational, middle, or senior managers, etc.) and judgments on routine working processes. All rules should be coded in IF-THEN-ELSE statements or other computer language forms for execution on a computer and stored in the knowledge base.

(b) Inference mechanism. The reasoning architecture of rule-based systems has a rule base and an inference engine that performs inferences (e.g., forward or backward chaining, or a combination of these two) (the general reasoning process of a rule-based system is shown in Figure 2.2). Given a new case, applicable rules are first found by matching against the rules of the rule base. Then intermediate results are generated by the chosen inference mechanism. The process is repeated until the desired solution state is reached.

There are two kinds of reasoning—forward chaining and backward chaining. Forward chaining is a data-driven reasoning. When it starts to infer rules, it always...
begins with the topmost rule, uses the known data, and proceeds forward with those data. The inference engine compares each rule stored in the knowledge base with facts in the database. When the IF (condition) part of the rule matches a fact, the rule is fired, and its THEN part (action) is executed. Once a rule is fired, the rule adds a new fact to the database. Any rule can be executed only once. The match-fire cycle stops when no further rules can be fired. Backward chaining is a goal-driven reasoning, in which the inference engine first has a goal and attempts to find evidence to prove it. The inference engine starts by searching for rules that might produce the desired solution and achieve the goal in the THEN (action) part (Wen et al., 2005).

![Figure 2.2 RBR Process (from Pal and Palmer, 2000)](image)

(iii) Integration of RBR and CBR in KBS Development

Based on the review of performance measurement study, one can note that many knowledge and information sources for the execution of performance measurement cannot be performed only in the form of rules. For example, business
professionals may analyze present business situation by reviewing and revising targets and standards together with previous experiences. Hence, the development of knowledge retrieval and inference mechanism should focus on the use of both RBR and CBR into the area of performance measurement (Pal and Palmer, 2000). In general, there are three different ways to combine RBR and CBR: (i) keeping RBR and CBR as two ‘‘equal’’ reasoning modules, (ii) letting the CBR module use the inference capability of rules when needed, and (iii) letting the RBR module dominate and use CBR categorically at particular points in the reasoning process. In this research, the knowledge retrieval mechanism of the proposed system is developed by integrating the CBR and RBR technologies and adopting the way, (ii) which is to let the CBR module use the inference capability of rules when needed. However, to ensure that the proposed system can deal with changes in performance and dynamic circumstances of the production shop floors, the knowledge source and information within the knowledge repository need to be updated. Real-time data collection technologies, including RFID and sensor, are used to capture different operations data such as machine operations status, material handling equipment, WIP, and other information in the production shop floor. The concept and application of RFID and sensor technologies are discussed in the following section.

2.4.4 RFID and Sensor Technology in the Manufacturing Industry

RFID is an automatic identification method used to store and remotely capture data using devices called RFID tags. RFID is an emerging data capture technology that has brought a lot of benefits to PAM in manufacturing companies. In recent years, a number of researches have shown the value, deployment, and implementation of RFID technology into logistics operations, particularly in inventory management (Kang and Gershwin, 2005; Lee and Ozer, 2005; Wal-Mart,
RFID technology helps to track the location of inventories automatically in a real-time manner. It eliminates the manual data input process and reduces inventory loss. In real practice, many enterprises are noted to have obtained the inventory cost minimization by using this technology. For example, Wal-Mart, one of the largest retail shops in the United States, has been using RFID/EPC system on pallets and cases handling since 2005 and has since then obtained a 16% decrease in the out-of-stock rate (Wal-Mart, 2005). By taking the RFID special characteristics of real-time data capture, a full traceability and visibility on tagged object status is provided. Through tracking the movement of WIP goods by RFID, the production process flow of manufacturing companies can be identified and managed. In addition, it supports performance measurement by providing accurate data of physical asset operation to measure production performance as well as efficiency of material handling equipment. The following cases include the RFID/sensor application in the manufacturing industry.

Case 1—Improving the traceability and visibility of mass customization manufacturing processes

Chen and Tu (2009) proposed a multi-agent system framework using ontology and RFID technology to monitor and control dynamic production flows of just-in-time (JIT) and just-in-sequence (JIS) manufacturing processes. A case study of a company manufacturing bicycles is recorded to demonstrate the concept of the system framework. The company currently uses paper travelers (run cards) with bar code labels for tracking and identifying thousands of work pieces (bicycle frames) moving around its production facility each day. Tracking and tracing its manufacturing process information involve human intervention which often causes errors and information delay. These problems further affect its process quality control.
To solve the problems, the company adopted the system framework proposed by Chen and Tu (2009). Results showed that the overall manufacturing process monitoring and control was improved with RFID technology. These improvement areas include: accuracy of data retrieval, real-time process information, reliability of the tag, replacement of human labor in data collection and tracking, allowing detailed tracking and tracking of process status, input/outputs, and the time that each processing step was performed and automatic scan without line of sight. Furthermore, the findings reveal that the prototype system can provide both shop floor operator and production supervisor with real-time production process information, helping them to respond to the status of the production line in real time and make better decisions in handling production events.

Case 2—Improving the logistics process flow in complex manufacturing processes

Thiesse and Fleisch (2008) investigated the benefits of a real-time location system (RTLS) using active RFID technology in production logistics. The study recorded real-world implementation of an RFID-based real-time location system for process control in a highly complex wafer fab manufacturing process. In the case of Infineon Technologies, it is a practical example of such an application area of RFID-based real-time location system (RFID-RTLS) with many process and product variants, extensive manual activities, and a large number of physical objects in a complex production system. In RFID-RTLS, an active RFID was selected as the foundation for the desired solution because of the battery requirements and communication performance. Owing to insoluble problems with electromagnetic reflections, ultrasound sensors were selected for fine-grained tracking. At the production floor, the ultrasound emitters located on the ceiling periodically sent a signal received by active RFID transponders, which are equipped with ultrasound
sensors. The tags calculate the time of flight for all received signals and store these values in their read-or-write memory. RFID controllers read these data and the lot’s identification number from the tags and transfer them to a central server that generates location information for all objects in the system. The server, again, continuously transfers lot locations to the fab’s tagged objects. With the help of the RFID-RTLS, the location visibility of lots in the fab has increased from 65% to 100%. The use of a RTLS can lead to significant improvements with regard to process performance indicators such as cycle time, machine utility, etc. This research not only demonstrates the development of process control procedures that use identification technologies, location sensing, and other sensor data on the physical processes on the shop floor, but also develops novel dispatching rules that consider real-time information on the logistics processes in the shop floor, thereby improving production efficiency.

Case 3—Enhancing the functionality of the tradition quality assurance system using RFID technology

Lyu et al. (2009) presented a novel framework for integrating RFID technology in a Quality Assurance System (QAS) to improve its effectiveness. The QAS framework includes shop floor and customer service (marketing). Product quality typically improves when feedback mechanisms are in place. In the manufacturing process, producing poor-quality products is unavoidable. The QAS prevents bad products from being manufactured or assembled further. The appropriate procedures must be established to manage quality in all departments, including sales, design, materials, and manufacturing. Quality control mechanisms require continual assessment through quality investigations or audits. By utilizing RFID, the QAS is able to detect, and even prevent, quality problems more effectively than the
traditional quality assurance system can. The proposed framework allows on-site staff to monitor complicated variations in production process by handling numerous possible abnormalities simultaneously. For example, Goodyear adopted RFID to track retail racing tires from the warehouse to the race track. Goodyear sells 2.2 billion tires annually, and scanning barcodes requires substantial manpower and time. By inserting RFID technology into the QAS, the rate of the daily quantity output increased from $8,767 - 15,068$ pieces to $10,256 - 17,628$ pieces, and manpower working days decreased from $5.3 - 9.1$ hours per day to $0.09 - 0.15$ hours per day. A tire pressure monitoring system reduces accidents and is now a standard RFID application. A manufacturer that combines the ability to collect tire pressure and temperature data by RFID tags can increase its product value, strengthen its IT production system, and record all production information, thereby overcoming the problems in collecting production information. With timely collection of production records, the IT production system can enhance tire quality, increase the benefit of tracking circulation and management of suppliers.

Case 4—Reducing the shop-floor WIP inventory and smoothening the flow at the fixed-position assembly islands

Huang et al. (2007) stated that real-time shop-floor information visibility and traceability offered by wireless manufacturing technology such as RFID, auto ID sensors and wireless information networks enable the implementation of JIT manufacturing to reduce shop-floor WIP inventories and to smoothen their flows through real-time information visibility and traceability. In Huang et al.’s (2007) study, an ultra-high-frequency RFID technology for real-life implementation was recommended because of its affordable cost and practically acceptable reading capability (e.g., distances and speed). For the RFID tag, pallets of WIP are tagged
and become smart objects, which are traced and tracked in the shop floor. The tags contain information about what module the object is involved with and its quantity. Tagged pallets are reusable, thus reduce tagging costs. For the RFID reader setup, to minimize the number of readers (and thus cost), it is decided to attach readers to (a) vehicles directly used for moving module pallets and (b) vehicles that carry toolboxes. They are also tagged to be smart vehicles. In addition, shop floors are networked with wireless devices deployed in important areas to ensure coverage. This is an inexpensive approach and avoids the wiring efforts and inconvenience caused by wiring. Wireless networking is important for real-time information visibility and traceability. Any changes are recorded in the backend systems and reflected in the frontend operators. This will further enhance other decision support systems. Based on the above suggested RFID setup, two typical limitations suffered by the fixed-position assembly islands, namely, limited spaces at work centers and high dynamics of material and manpower flows, are overcome while retaining necessary flexibility. The main contribution of this research is the presentation of an affordable, wireless manufacturing solution to reduce the shop floor WIP inventories and to smoothen their flows.

Case 5—Improving the quality control of headlamp lenses using a sensor planning system

Most production plants are equipped with sensors providing information to a control room where operators monitor the production process. Based on their skills and experiences, the operators are alerted if something unusual happens; the results of this manual inspection depend on human factors that subjectively lead to a dissatisfactory quality control. Martinez et al. (2009) developed a sensor planning system to apply the quality control of headlamp lens in automotive lighting industry.
In a manual inspection procedure of headlamp lens, once a defect has been revealed and located, it must be classified as acceptable or rejectable by looking up the inspection guideline and judgment of the worker. In some manner, this definition is subjective and depends on such aspects as the experience and perception of the expert. To alleviate the quality control problem, a sensor planning system uses the lens CAD, a vision sensor model and the customer requirements, included through a fuzzy approach, to achieve an optimal set of viewpoints. A vision sensor model uses a pin-hole lens to capture the image of the geometrical properties of headlamp lens. The results show the effectiveness of the sensor planning system on quality control of commercial lenses.

From the above case studies, it is observed that the application of RFID/sensor technology improves the quality and production efficiency of the shop floor center. By utilizing the real-time data captured by the RFID/sensor technology, the system ability and decision support accuracy focusing on different aspects are enhanced. In addition, the characteristics of automatic scan without line of sight of these data capture technology provide great potential benefit to the performance measurement by replacing human labor in data collection on machine, WIP, and finished goods at the production shop floor.

### 2.5 Summary of the Literature Review

In the previous sections, the works of researchers who examined the background study of PAM in manufacturing industry and performance measurement have been discussed. The review shows that enterprises can exploit PAM strategy to achieve the greatest lifetime effectiveness and utilization from their physical assets so as to optimize productivity and improve profitability. Currently, most researchers view PAM only from the maintenance perspective, hence ignoring the asset
operations ability and performance evaluation. PAM is no longer confined to maintenance issues only; its scope should be extended to include measuring and evaluating the asset operations and performance.

The essential function of a performance measure is to assess how well the activities within a process or the outputs of a process achieve specified goals. Among the frameworks and models discussed in Section 2.3.2, it is found that various researchers frequently used cost, quality, time, and flexibility as four core dimensions for manufacturing performance. From the point of view of PAM, which focuses on enhancing machine capability and lifetime effectiveness, machine flexibility (MF) is the most important dimension to be considered. MF is defined as the set of all operations in a reference set that a machine can perform with a positive degree of efficiency. MF shows how easily a particular machine can adapt to changes and uncertainties, such as machine breakdowns, heavy load, different sequence or dispatching rules to reduce setup time. Based on the review of MF, it is noted that technological attributes are performance indicators of different resources and activities in a manufacturing system. To enable accurate measurement of MF, the implementation of performance measurement systems (PMS) should be incorporated with data collection and analysis technologies, which can measure the above technological attributes. To do so, a PMS should be developed with the support of information technology (IT), business intelligence solution, and knowledge-based systems.

In Section 2.4.2, there are a number of approaches and systems that have been designed and implemented to support performance measurement in manufacturing. It is found that artificial intelligence (AI), data management, and mining techniques are promising technologies to develop an expert system and KBS for modern manufacturing enterprises to support different aspects of performance measurement.
In order to accurately reflect current complex production environment, the KBS should be incorporated with RFID/sensor technology for capturing real-time manufacturing data on the production shop floor. Research studies about RFID and sensor application on the manufacturing industries were discussed in Section 2.4.4.

This research proposes a knowledge-based performance measurement system (KPMS), which supports the decision-making processes of performance measurement planning and machine flexibility assessment. The proposed system is developed by AI and RFID/sensor technologies. The detailed system framework, design steps and mechanism are discussed in Chapter 3.
Chapter 3 The Knowledge-based Performance Measurement System (KPMS)

3.1 Introduction

The design of a knowledge-based performance measurement system (KPMS) is discussed in this chapter to support the decision-making processes involved in production planning and machine selection when encountering unpredictable problems at the production shop floors. The proposed system is developed by artificial intelligence (AI) and certain real-time data collection technologies aiding to solve the production planning and machine selection problem. During the production planning for different customer requirements, the proposed system supplies the production planner with accurate knowledge and information, including operations workflow, resource capability level assessment, historical quality problem, maintenance plan, and production cost and time estimation. The provision of above information and knowledge can significantly improve production planning time and reliability. On the other hand, a machine flexibility assessment function is proposed in the KPMS for solving machine selection problem. By assessing machine flexibility, the production planner can acquire the knowledge necessary for each machine’s performance on different products to select the right machine during emergent situations such as machine breakdown on the floor. In the KPMS architectural design, case-based reasoning (CBR) is adopted to develop the core module and derive useful knowledge from the manufacturing operations data, customer data, and performance indicators collected from the production floor. CBR plays a critical role in facilitating knowledge management initiatives such as knowledge retrieval and storage during the production planning process. Apart from this AI technique, RFID and sensor technologies are incorporated and adopted to
capture real-time production data from the production asset.

This chapter is divided into four sections. The proposed KPMS is introduced in Section 3.1 while its overall architectural design and framework are presented in Section 3.2. Section 3.3 describes the RFID and sensor technologies’ data collection modules as well as data warehouse manipulation. Finally, the development of KPMS core module is discussed in Section 3.4.

3.2 KPMS System Architecture

The KPMS is designed to support knowledge management initiative and decision support for manufacturing planning, thereby enhancing the production floor’s efficiency. The proposed system likewise enables the production planner to conduct real-time monitoring of the machine performance in various functional areas. Thus, the target users of the proposed system are production supervisors and managers, who need to prepare production planning and machine selection as well as evaluate performance of physical asset operation. The KPMS’ generic architecture is illustrated in Figure 3.1.

The KPMS consists of two modules, namely, Radio Frequency-based Manufacturing Data Collection Module (RFMC) and Knowledge-based Performance Measurement Module (K-PM). These are developed to support the proposed system’s functions. For the first module, RFMC is responsible for managing real-time manufacturing data by utilizing RFID, sensor, and data warehouse technologies. RFID is adopted to capture real-time data, including work-in-progress goods’ identity and resource operations status and location. Sensor is selected to collect data related to the machine operation’s characteristics. Data warehouse is a data management technology responsible for managing large amount of operations data.
For the second module, K-PM is a KPMS core module. This module comprises two sub-modules with a knowledge repository to provide knowledge-based decision support for production planning and machine selection. The KPMS’ detailed mechanism is discussed in Sections 3.3 and 3.4.

Figure 3.1 The Generic Architecture of KPMS

3.3 Radio Frequency-based Manufacturing Data Collection Module (RFMC)

This module is designed primarily to collect, transmit, and control manufacturing data from the production shop floor required for supporting performance measurement and production planning. It is responsible for managing different data of machines and products as well, to support the K-PM core module’s functionality. The RFMC module mainly adopts two kinds of data capturing technologies: RFID and sensor. RFID is an automatic identification technology
applied for identifying and tracking products’ real-time locations, including raw materials, work-in-process (WIP) goods, and finished products within different production floors and warehouses. Sensor technology is mainly employed to collect raw data from production machines on the shop floor to detect their operation status and measure their performance.

**3.3.1 RFID Technology for Real-time Manufacturing Data Collection**

In the RFMC module, RFID technology is adopted to collect, process, and transmit manufacturing data from the production floor to the data warehouse by automatically identifying production items through radio frequency signals. As **Figure 3.2** demonstrates, a typical RFID system is composed of several components, namely, tags, antennas, reader, and host computer system.

![RFID System Architecture](image)

**Figure 3.2 Architecture of an RFID System**

Tags are devices attached to objects that require tracking on the production floor, such as WIP goods. Antennas transmit and receive electromagnetic signals between the tags and the reader. The area with effective electromagnetic field is known as the interrogation zone, while a reader creates an electromagnetic signal sent to the RFID tags through antennas. Antennas and RFID readers installed in proper locations can recognize the presence of RFID-tagged WIP goods and read the information stored in the tags if the RFID tags are within the interrogation zone. Data captured by the
reader is then conveyed to the host computer system, in which software applications such as RFID middleware can filter the data and integrate these to the correct enterprise applications. Two factors must be considered when choosing an RFID system for applications: passive/active RFID system and RFID frequency band used for application.

(i) Passive/Active RFID System

When applying RFID technology in the RFMC module, two types of RFID system may be considered: passive and active. As illustrated in Table 3.1, the passive RFID system does not have an internal power source in its tag while the active system’s tag is integrated with a battery. Because the passive system’s tag does not have a battery, it is smaller in size and is priced lower.

<table>
<thead>
<tr>
<th>Comparison factors</th>
<th>Passive RFID system</th>
<th>Active RFID system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Presence of internal power</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>source in RFID tags</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost</td>
<td>Lower</td>
<td>Higher</td>
</tr>
<tr>
<td>Physical size of RFID tag</td>
<td>Smaller</td>
<td>Larger</td>
</tr>
<tr>
<td>Operational life</td>
<td>Longer</td>
<td>Shorter</td>
</tr>
<tr>
<td>Read range</td>
<td>Shorter</td>
<td>Longer</td>
</tr>
<tr>
<td>Data storage</td>
<td>Less</td>
<td>More</td>
</tr>
</tbody>
</table>

The passive RFID system’s operational life is longer compared to the active RFID system because battery replacement is not required. However, the active RFID system’s read range is longer and more data can be stored in its tags. In the RFMC module, the RFID system is primarily utilized on the production floor to collect real-time manufacturing data. This is achieved by tracking WIP goods processed by
different shop floors. As the objects to be tracked are WIP goods, RFID tags that record their identity should be attached so they can be identified by the reader and antenna. Since WIP goods’ physical appearance varies among different kinds of products and the possible areas for attaching the tag are limited, smaller RFID tags are preferred.

Further, given the sizeable number of WIP goods on the production floor, many RFID tags are required in the system. To reduce implementation cost, passive tags with lower cost and longer operational life are considered for the RFMC module. Although the passive tags’ read range is relatively shorter compared with active tags, it satisfies the purpose of tracking WIP goods in various locations such as portals, storage areas, and machine cells. Meanwhile, because of passive tags’ limited data storage memory, simple information such as unique product ID can be recorded. The RFID system can then be linked to an external database for more detailed information by referring to the unique product ID. After examining these factors, the passive RFID system is selected for the KPMS’ RFMC module.

(ii) **RFID Frequency Band Used in Application**

As RFID technology leverages radio frequency signals to capture data from tags within a certain read range, the selection of RFID frequency bands is another critical factor to consider when applying RFID in different applications. As illustrated in Table 3.2, there are four types of RFID frequency bands: low frequency (125–134 kHz), high frequency (13.56 MHz), ultra high frequency (860–960 MHz), and microwave (2.45 GHz). The low-frequency read range is the shortest and its tag cost is high, but it possesses a better read rate near metal or liquid compared with other frequency bands. The tag cost of high frequency is less expensive but its read range is quite short. It is suitable for applications that do not require reading multiple tags.
within a long distance, such as access control and libraries. Meanwhile, the tag cost of ultra high frequency is the lowest and it can read a large number of tags within a long read range, specifically between 3m and 7m. The read range of microwave is the longest and its read rates are faster, but its tag cost is high and its reading performance is easily affected by metals and liquids.

Table 3.2 Comparison of RFID Frequency Bands (Adapted from Kwok et al., 2007)

<table>
<thead>
<tr>
<th>Frequency band</th>
<th>Frequency range</th>
<th>Typical read range</th>
<th>Tag cost</th>
<th>Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Frequency (LF)</td>
<td>125–134 kHz</td>
<td>&lt;5cm (Passive)</td>
<td>High</td>
<td>Access control, animal identification</td>
</tr>
<tr>
<td>High Frequency (HF)</td>
<td>13.56 MHz</td>
<td>10 cm – 1 m (Passive)</td>
<td>Medium to Low</td>
<td>Access control, apparel, baggage tracking, libraries, smart cards, transport</td>
</tr>
<tr>
<td>Ultra High Frequency (UHF)</td>
<td>860–960 MHz</td>
<td>3 m – 7 m (Passive)</td>
<td>Low</td>
<td>Baggage tracking, electronic toll collection, pallet and case tracking, supply chain management and logistics</td>
</tr>
<tr>
<td>Microwave</td>
<td>2.45 GHz</td>
<td>10 m–15 m (Passive) 20 m–40 m (Active)</td>
<td>High</td>
<td>Access control, container tracking, electronic toll collection, smart cards</td>
</tr>
</tbody>
</table>

Comparison of the four frequency bands revealed that ultra high frequency is the most suitable for the KPMS’ RFMC module because of its low tag cost and long read range. In the application of KPMS, a number of WIP goods are tagged and their locations are tracked when moved between production floors. Since a number of RFID tags are needed and the distance between tagged WIP goods and tracking points such as shop floor portals and machine cells is normally long, ultra high
frequency should be employed to reduce tag cost and read multiple tags within a long read range.

To deploy RFID technology in the KPMS' RFMC module and implement it on the production floors successfully, the following eight steps are suggested, as demonstrated in Figure 3.3.

![Figure 3.3 Steps of RFID System Deployment](image)

**Step 1: Understand current production processes**

Before deploying RFID technology, the manufacturing company’s current production processes and workflow should be understood clearly. This can be achieved by conducting daily observations on the production floor as well as interviews with factory managers and workers. Flowcharts should be drawn to illustrate the production workflow.

**Step 2: Determine the requirements of RFID tracking**

Once the production processes are understood, the requirements of RFID tracking should be determined. The manufacturing company should determine which production processes or shop floors require the RFID tracking system’s installation. Decisions must be based on the purpose of implementing RFID solutions such as
reducing inventory loss, monitoring the progress of significant manufacturing processes, and increasing data visibility. Moreover, it should determine the types of products and items that need to be tracked in the RFID system. For example, it can track certain expensive products and WIP parts to avoid loss. It can likewise track the products availed of by preferred clients to enhance customer satisfaction and loyalty.

Once the items to be tracked are identified, the locations for setting up the RFID tracking points should be considered. Portals of production floors normally prove to be the ideal location for tracking points because installation of equipment in these areas will not hinder operations. On the other hand, if the manufacturing company intends to collect real-time manufacturing data from a particular machine to monitor its performance, then a RFID tracking point should be mounted on the machine cell.

**Step 3: Select suitable RFID equipment**

Once the requirements for RFID tracking are identified, the number of RFID equipment including tags, readers, and antennas can be estimated. Suitable RFID equipment should then be selected to fulfill the RFID applications’ requirements.

(a) **Tags**

RFID tags come in different shapes, sizes, and capabilities. They differ in three main aspects: power source, tag frequency, and writing capability.

- **Power sources**

  RFID tags require a power source to communicate information to the reader through antennas. Currently, three kinds of RFID tags powered by different sources are available: passive, active, and semi-passive tags. Passive tags do not possess an internal power source as they rely on obtaining electromagnetic power from the reader and antenna to transmit a signal. The passive tags’ reader can be simpler, smaller, and less expensive. Active tags, meanwhile, are equipped with a small
battery that supplies the power. They are larger and more expensive. However, active tags possess a longer read range than passive tags. Owing to their large size and high cost, active tags are seldom utilized in small, high-volume, and low-priced products. In the case of semi-passive tags, an internal battery is embedded to power their internal circuitry, including sensors for monitoring environmental conditions such as temperature, humidity, and vibration. However, this is not utilized for communicating with the antenna and reader. For data communication, they mainly rely on the electromagnetic field power generated by the reader and antenna, which is the same as passive tags.

- **Tag frequencies**

  RFID tags primarily operate in high frequency (HF) and ultra-high frequency (UHF). The selection of HF tags or UHF tags in applications should consider the required read range and material in the applications. HF tags’ read range is limited to several inches but UHF tags’ read range can be extended to several feet. The material used in the applications is a critical issue when selecting RFID equipment, as certain materials deflect radio frequency, such as metals, while some absorb it, such as liquids. Radio frequency reflecting materials deflect the radio frequency wave so that the tag antenna cannot absorb sufficient energy to be powered and transmit signal. Meanwhile, radio frequency absorbing materials absorb the radio frequency energy to reduce the signal’s strength. Thus, the tag cannot be activated because of insufficient power. The HF tag is better than UHF in terms of the ability to read near metal or liquid.

- **Writing capabilities**

  The writing capabilities of certain RFID tags are different. Generally, there are three kinds of writing capabilities: read-only; write once, read many (WORM); and read/write. Read-only tags contain the identification data specified and entered by the
tag’s manufacturer; as the name suggests, it can be read only. WORM tags provide buyers with an opportunity to write identification data onto the tag, but data cannot be modified once it is written. Read/write tags can be programmed by buyers and their identification data can be changed and reprogrammed.

(b) Reader and antenna

Apart from RFID tags, RFID reader and antenna should likewise be selected according to the RFID application’s needs. The RFID reader sends radio frequency signals through the antenna to power the tags. Simple handheld RFID scanners may be employed in situations where users need to individually scan the objects. Stationary RFID readers may be adopted in conveyors or loading dock portal applications where they are mounted on a wall, doorway, or other location; the tracking objects will move and pass them rapidly. The size of the interrogation zone and radio frequency field generated by the reader are controlled by RFID middleware installed in the host computer system. The antenna will transmit radio frequency signal from the reader to the tags and subsequently receive signal from them. The number of antennas employed in each tracking point should be considered carefully. If the tag’s orientation towards the reader does not change, then a single antenna will suffice. However, if the tag’s orientation changes, then more than a single antenna should be used to increase the read rate’s accuracy. For example, it is common to install an antenna on each side of the door when an RFID gateway is set up in portals.

Step 4: Conduct on-site experiments

After selecting suitable RFID equipment for specific applications, it is critical to conduct on-site experiments to evaluate an RFID system’s reading performance in a
deployment site. The RFID Deployment Optimizer (RFID-DO), a patented software developed by Kwok et al. (2007) for benchmarking RFID configurations, is utilized to determine the configuration’s performance accurately and reduce the RFID system’s full deployment time. RFID-DO helps to collect objective quantifiable data of tag reading performance in the site to compare and optimize the RFID application under actual deployment environment and operational flow. It involves two analytical methodologies, namely, Interrogation Zone Analysis (IZA) and Tag Placement Analysis (TPA). IZA assists in evaluating a deployment site’s environmental effects for an RFID configuration’s optimizing performance. It reports and visualizes readability performance profile in an interrogation zone in the form of contour map and surface diagram. Meanwhile, TPA helps to identify RFID tags’ optimal placement on the target product under actual operational conditions. It captures tag dynamic readability performance data when the tagged product is passed through the RFID gateway; data is visualized as a line graph. To apply RFID technology on the KPMS’ RFMC module for capturing real-time manufacturing data from the shop floor, the following experiments should be conducted in the deployment site. These are geared towards optimizing the RFID configurations’ performance.

- Determine the setting antennas’ height

The RFID application for collecting real-time manufacturing data involves the installation of RFID gateways at the shop floors and warehouses’ portals, as well as in the machine cells. WIP goods with RFID tags are moved by shop floor operators to pass through RFID gateways during the manufacturing process. An experiment should be conducted to determine the height of antennas and provide an appropriate interrogation zone in each RFID gateway for reading tags accurately. If the antennas
are set at varying heights in the deployment site, the interrogation zone’s size and reading strength will vary as well.

To help determine the optimal height for antennas, the IZA of RFID-DO can be tapped for collecting the interrogation zone’s reading performance data under different settings. The antennas’ height can be determined by comparing the performance of different antenna settings and choosing the one with better reading results in the IZA.

- Compare the performance of different types of tag

Tag selection is one of the critical factors affecting the RFID deployment’s performance. There are a number of tag suppliers such as Alien Technology, Avery Dennison, Impinj, and Rafsec. Each supplier manufactures various types of RFID tags in different sizes, tag antenna shapes, and frequencies. Since the tag’s performance would be affected by certain opaque materials such as metal and liquid, it is necessary to test the reading performance of different kinds of tags after being attached to WIP subassemblies and components. Tag performance is compared by tapping the IZA of RFID-DO. By balancing various factors of consideration such as readability performance, cost, and ability to read near metal or wet surface, the most suitable type of RFID tags would be selected for deployment in the shop floors.

- Evaluate environmental factors in the site

In the RFMC module, RFID gateways are installed in different locations on the production floor, including portals and machine cells. This is conducted to automate manufacturing data acquisition when tagged WIP goods are moved by platform trucks, pallet trucks, or forklifts to cross the gateways. Since production floors have different kinds of machinery and equipment with metal and liquid contents, the radio
wave emitted from the reader may be deflected and scattered by metal or absorbed by liquid contents in the shop floor environment. Therefore, an experiment is essential to evaluate these environmental factors by studying the reading performance in the IZA after RFID configurations are installed.

- Determine the tag placement’s best location and orientation

  In a typical manufacturing process, WIP goods and components are placed in cases, boxes, trays, or portable racks and moved across different shop floors and machine cells for processing. Depending on the products’ characteristics, RFID tags can be embedded in each WIP good at the item level or placed in boxes and trays storing WIP goods and components at the case level. Further, the tag may be placed in a vertical or horizontal orientation and on different sides of objects, be it on the front, side, or corner. To ensure the high readability of RFID tags placed on WIP goods or their cases, several tags should be placed in different orientations and locations, and the TPA of RFID-DO should be performed to determine the best location and orientation for the RFID tag.

- Determine the suitable height for placing tagged objects in passing RFID gateways

  As WIP goods and components are placed in cases or boxes for transport to different locations, they may be stacked on pallets or platform trucks and moved by shop floor workers to cross RFID gateways. If the tagged WIP goods or cases are stacked too high, they may be outside the interrogation zone or receive very weak radio frequency signals from the field. Thus, reading performance will be affected significantly. To avoid decline in readability, height should first be tested and determined. This can be achieved by placing tags on cases located in different layers.
and comparing their reading performance in the TPA of RFID-DO.

**Step 5: Prepare guidelines and working procedures**

Once the RFID system is implemented on the production floor, new working procedures will be introduced in the manufacturing process. For example, shop floor workers need to attach an RFID tag to a designated location of WIP goods during the manufacturing process. They likewise need to ensure that the tagged goods will pass through RFID gateways when being transferred in and out of the production floor. To communicate the new working procedures effectively to workers, guidelines for implementing RFID measures on the floor should be prepared and enforced.

**Step 6: Provide staff training**

As human resource is one of the critical success factors in RFID implementation, it is important to provide staff training to achieve full understanding of the objective behind RFID system implementation on the floor and the employees’ roles and responsibilities in maintaining the RFID system. New working guidelines after RFID system implementation are communicated to the staff during training.

**Step 7: Conduct pilot run and evaluation**

A pilot run of RFID system should be conducted to obtain data for evaluating RFID deployment’s operational performance in an actual production site. Shop floor workers are involved in the pilot run to identify any potential problems prior to actual implementation.

**Step 8: Implement the RFID system**

After the pilot run and system evaluation, RFID configurations should be
revised if necessary. When the RFID system’s performance is satisfactory, then it should be implemented on the production floor to obtain real-time manufacturing data.

As mentioned above, passive RFID system is adopted in the KPMS’ RFMC module to collect, process, and transmit manufacturing data to the data warehouse. A passive tag consists of an integrated circuit for storing item identity and other information. It is attached to items on the production floor such as WIP goods, cases, or pallets to record the identity of products and material. On the other hand, the RFID reader is integrated to fix positioned antennas mounted on different areas of the production floor, including the door frames of shop floor portals, warehouse portals, and machine cells for detecting and recording the tagged items’ movement through the course of production. When a number of tagged WIP goods are transferred between different shop floors and passed through an RFID gateway, their identity, location, and processing time are read by the antennas within the interrogation zone. Thus, the manufacturing data of actual production process flow, production time, yield rate, and quantity of inventories are collected automatically by the RFID system. Further, when an RFID gateway is set up in machine cells, it can recognize the identity of products processed by the machine. This helps to identify the machine’s production period in processing different production orders for determining its flexibility in producing different product types. Although RFID technology is adopted to recognize the product types processed by a machine within a different time period, it does not capture the manufacturing data related to the machine’s physical performance, such as uptime, downtime, cycle time, and throughput. To capture information on machine status, sensor technology is employed in the KPMS’ RFMC module, as described in the following section.
3.3.2 Sensor Technology for Real-time Manufacturing Data Collection

According to Hauptmann (1993), a sensor converts physical dimension, which is to be measured into an electrical dimension that can be processed or transmitted electronically. Sensor is utilized for sensing, converting, and recording of measured values and gaining all the information required in connection with process status and environment. Examples of physical dimensions that can be converted into electrical signals by a sensor are thermal signals, mechanical signals, magnetic signals, electro-magnetic radiation, and chemical volumes. As Figure 3.4 illustrates, technical sensors are employed to convert a machine’s physical status, such as temperature and pressure, from being non-electrical into electrical signal. Subsequently, the electrical signal needs to be processed and prepared, including amplification, filtering, and linearization. It likewise needs to be processed by actuator control and regulation in order for the system to obtain and display a machine’s status. As signal processing and preparation are an important stage in obtaining useful information from sensors, there are several types of sensor systems with different signal preparation electronics that can be selected for application.

As illustrated in Figure 3.5, the first type is a sensor system with discrete construction of signal preparation electronics. The electronics of signal preparation is separated from the sensor. The second type is a sensor system with an integrated sensor. In an integrated sensor, the signal preparation electronics is integrated with the sensor to filter and process the signal. The third type is an intelligent sensor that includes both the integrated sensor and processing units, allowing the implementation of correction algorithms, diagnostics, tests, or selective polling of different sensors. Further, to select a good sensor for application, the following characteristics can be used as selection criteria: adequate sensitivity; high degree of accuracy and good reproducibility; high degree of linearity; good dynamic range;
insensitivity to interference and environmental influences; high degree of stability and reliability; and long-life expectancy and problem-free replacement (Tschulena and Selders, 1983).

![Figure 3.4 Technical Sensors for Data Capture (Adapted from Hauptmann (1993))](image)

![Figure 3.5 Types of Sensor Systems: (a) Sensor System with Discrete Construction; (b) Sensor System with Integrated Sensor; (c) Intelligent Sensor (Extracted from Hauptmann (1993))](image)

In the proposed KPMS’ RFMC module, sensors are primarily utilized to capture the physical status of machines on the production floor, such as operation, setup, and failure time period. Depending on the machines’ characteristics, various types of sensors can be utilized to collect data from the machines’ physical status. Examples of sensors are temperature sensor, pressure sensor, optical semiconductor sensor, magnetic field sensor, vibration sensor, ultrasound sensor, and switch for detecting...
changes in distance or angle. For example, if temperature is a key dimension for detecting the machine’s status, then a temperature sensor is embedded in the machine to measure temperature changes within different time periods. If the machine vibrates during the production process, then a vibration sensor is utilized to detect the frequency of vibration. If the displacement of a machine component is a critical process status, then a switch or a magnetic field sensor, which serves as a contact-free switch, can be employed to sense the changes in the component’s location. After suitable sensors are embedded in the machines, physical dimensions such as temperature, pressure, acceleration, vibration frequency, current, voltage, and mechanical separation are captured, processed, and transformed into useful data and information. These data will reflect the machines’ operational conditions and measure the performance of production process. By applying sensors to detect machine status such as the start and end of operation, setup, and breakdown, and recording their corresponding time intervals, several performance indicators of the machine and production performance including cycle time, machine availability, breakdown frequency, and throughput can be determined.

After manipulation and processing, the manufacturing data obtained from sensors and RFID are stored in a data warehouse. This is responsible for storing information on machine conditions, locations, and quantities of WIP goods and production processes, as well as other information required for supporting the performance measurement function in the system’s K-PM module.

3.3.3 Data Warehouse for Management of Manufacturing Data

The data warehouse is a centralized relational database for integrating, managing, and storing manufacturing data from RFID and sensor data collection modules, enterprise applications such as enterprise resource planning (ERP) system,
and other documents from the production, quality control, and engineering departments. The manufacturing data stored in the data warehouse is used for supporting the KPMS core module, the K-PM module, in measuring manufacturing performance by various key performance indicators and calculating machine flexibility. As illustrated in Figure 3.6, four steps are designed to manage and store the manufacturing data from different sources into the data warehouse.

![Steps in Data Management and Storage in Data Warehouse](image)

**Figure 3.6 Steps in Data Management and Storage in Data Warehouse**

**Step 1: Integrate data from different sources**

The manufacturing data required in the KPMS are obtained from different
sources. For example, real-time data of WIP inventories’ location and machines’ status in various shop floors are captured by data collection technologies of RFID and sensor, respectively. Production details such as product information, customer requirements, and production order information are maintained in the ERP system. Moreover, information on product quality, maintenance, and specifications of production machines are located in different documents. Examples of such documents are quality control report and maintenance report, which are scattered in various departments including quality control, production, and engineering. As these manufacturing data are important for supporting machine performance assessment and decision making during production planning, data are integrated from various sources into the KPMS’ data warehouse. A code is assigned to represent each production floor and department to identify data coming from their sources.

**Step 2: Filter duplicated data**

As the RFID and sensor technologies capture raw data from continuously tracking WIP inventories and machines, the raw data includes many duplicated and irrelevant records and noises that are meaningless to the enterprise application, thus affecting data accuracy. Therefore, raw data collected from RFID and sensor need to be filtered by RFID middleware and signal processing technique, respectively, to remove the duplicated data and ensure that only relevant and meaningful information is stored in the data warehouse.

**Step 3: Standardize data format**

Since manufacturing data are integrated from various systems, and documents are prepared by different departments, it is inevitable that the formats employed in these data are different. Examples of inconsistent data formats are the presentation of
date, number, currency, unit, word spelling and capitalization. To help the K-PM module retrieve data easily and accurately from the data warehouse, the format is standardized in this step.

Step 4: Correlate data

After data from different sources are integrated, filtered, and adjusted in standard format, they are stored in several relational tables utilized for keeping different categories of data such as product, customer, production order, machine, maintenance, and transaction. A unique primary key is assigned to each relational table. Data from different categories are correlated with each other by building relationship among the tables. This helps to reduce data redundancy in different tables and enhance data retrieval efficiency.

After the four steps of data management and storage, relevant manufacturing data and information from different floors and departments are integrated and stored in the data warehouse in a consistent and systematic format. It is utilized in the K-PM module for supporting the functions of performance measurement, production planning, and machine flexibility assessment in the proposed KPMS.

3.4 Knowledge-based Performance Measurement Module (K-PM)

K-PM is the proposed system’s core module. It provides knowledge manipulation for decision support on manufacturing planning and the selection of machines. This module consists of two submodules, namely, knowledge-based engine and machine flexibility assessor to support the above two decision-making tasks, respectively.
3.4.1 Knowledge-based Engine

A knowledge-based engine is developed to assist the manufacturing planner in evaluating the effectiveness of resource allocation, index value of the performance indicators, and operations workflow in accordance with company objectives. The engine not only assesses the effectiveness of the physical assets in performing the job orders and attaining the company objectives, but provides recommendations for improving productivity performance as well. The engine is built by rule-based expert system and CBR technology, which stores knowledge in the form of “if-then” rules and case form to solve manufacturing and asset allocation problems encountered on the floor. The knowledge-based engine consists of three parts: performance indicator analyzer, performance scoring model, and performance evaluation.

(i) Performance Indicator Analyzer

The performance indicator analyzer is built by the rule-based reasoning expert system to select the appropriate performance indicators for measurement. The knowledge of selecting suitable performance indicators is presented in the form of “if <antecedent clauses> then <consequent clauses>” statements. If the antecedent clauses are true, then the consequent clauses are true as well. The knowledge of evaluating and matching factories’ capabilities includes performance indicators setting and assessment, customer order requirement, matching criteria of indicators and requirements, and factory selection. Based on the knowledge rules, the performance indicator analyzer selects the relevant performance criteria and their involved key performance indicators according to the company objectives. Many companies tend to pursue certain objectives such as profitability, market share, customer focus, product quality, and productivity. Further, different customers are considered to have different requirements and expectation levels on products, and the
index values of each indicator are different. As demonstrated in Figure 3.7, different performance criteria including cost, quality, customer satisfaction, and efficiency, as well as corresponding performance indicators, are defined.

**Figure 3.7 The Hierarchical Structure of Performance Indicators Selection**

Examples of rules involved in the performance indicator analyzer are presented as follows:

**Rule 1:**

If Company_Objective = Profitability then Performance_Criteria = “Profit, Cost, Dependability, Quality”

**Rule 2:**

If Company_Objective = Productivity then Performance_Criteria = “Cost, Quality, Time, Efficiency”

**Rule 3:**

If Performance_Criteria = Cost then Key_Performance_Indicator = “Unit_Cost, Inventory_Cost, Running_Cost”

**Rule 4:**

If Performance_Criteria = Quality then Key_Performance_Indicator = “First_Pass_Yield, Defect_Ratio, Scrap_Rate”
The if-then rule structure considers the factories’ performance and customer order requirements and classifies them into different degrees of indicators. To allow discrimination between the degree values of two rules, rule priority is a preference criterion to solve conflict rules. A preference relation “>” is explicitly defined among rules. For example, given two rules, Rule 1 and Rule 2, Rule 1 will be preferred if its information content is more precise than that of Rule 2. Consider the example below:

Rule 1:

If Performance_Criteria = Cost_Manufacturing then

Key_Performance_Indicator = “Labor_Cost, Material_Cost, Scrap_Cost”

> Rule 2:

If Performance_Criteria = Cost then Key_Performance_Indicator =

“Unit_Cost, Inventory_Cost, Running_Cost”

Under this priority criterion, Rule 1 will be preferred over Rule 2 and the indicators in Rule 1 will be selected. Based on the above mechanism, performance indicators associated with defined company objectives/customer requirements are selected. Since the key performance indicators are selected by knowledge rules while the the knowledge rules and KPI hierarchies are determined through discussions between management level and operational staff of a company, different users may adjust the knowledge rules and KPI hierarchies in order to fulfill their actual needs. After selecting the performance indicators, the performance indicator analyzer examines operational data retrieved from the data warehouse and assigns scores to each performance indicator. The values of the performance indicators can be retrieved from the database directly or determined by equations. For example, the key performance indicator of defect ratio can be found in Equation 3.1.

\[
\text{Defect ratio} = \frac{\text{Defects}}{\text{Total production}} \tag{3.1}
\]
The number of defective units and total production units are retrieved from the database and calculated to obtain the defect ratio. Subsequently, the value of the performance indicator is analyzed together with decision rules retrieved from the rule base to assign a performance score to each indicator. An example of knowledge rules which assign a score to the defect ratio’s performance indicator is presented below:

Rule 1:
If Defect_Ratio < 5% then Performance = “Very Satisfied” and Defect_Ratio_KPI = 4

Rule 2:
If Defect_Ratio > 5% and Defect_Ratio < 10% then Performance = “Satisfied” and Defect_Ratio_KPI = 3

Rule 3:
If Defect_Ratio > 10% and Defect_Ratio < 20% then Performance = “Normal” and Defect_Ratio_KPI = 2

Rule 4:
If Defect_Ratio > 20% and Defect_Ratio < 40% then Performance = “Dissatisfied” and Defect_Ratio_KPI = 1

Rule 5:
If Defect_Ratio > 40% then Performance = “Very Dissatisfied” and Defect_Ratio_KPI = 0

(ii) Performance Scoring Model

The overall performance scoring model is employed to integrate all key performance indicators into an overall performance score according to appropriate weighting.
The parameters used in the model are presented below.

Parameters:

\( S \)         Overall performance score of a resource allocation decision
\( f_i \)       Performance score obtained related to the perspective of objective \( i \)
\( x_i \)       Weighting of the objective \( i \) to evaluate the overall performance
\( n \)         Number of objectives to be considered in performance measurement

\( KPI_j \) Score of key performance indicator \( j \)
\( w_j \)       Weighting of key performance indicator \( j \) to determine the performance score related to a particular objective
\( a \)         Number of key performance indicators that are required to determine the performance score related to a particular objective

The overall performance scoring model is presented in Equation 3.2.

\[
S = \sum_{i=1}^{n} f_i x_i
\]  \hspace{1cm} (3.2)

where

\[
f_i = \sum_{j=1}^{a} KPI_j w_j , \hspace{0.5cm} i = 1, 2, \ldots n
\]  \hspace{1cm} (3.3)

\[
0 \leq x_i \leq 1 , \hspace{0.5cm} i = 1, 2, \ldots n
\]  \hspace{1cm} (3.4)

\[
\sum_{i=1}^{n} x_i = 1
\]  \hspace{1cm} (3.5)

\[
0 \leq w_j \leq 1 , \hspace{0.5cm} j = 1, 2, \ldots a
\]  \hspace{1cm} (3.6)

\[
\sum_{j=1}^{a} w_j = 1
\]  \hspace{1cm} (3.7)
The goal of Equation 3.2 is to determine the overall performance score of a resource allocation decision, $S$, which is calculated by multiplying the score obtained in each objective perspective, $f_i$, with the weighting of that objective on overall performance, $x_i$. $x_i$ represents the relative importance of objective $i$ in evaluating the overall performance. It is determined by the managers when they input the requests of performance measurement. As Equation 3.3 illustrates, $f_i$ is obtained by multiplying the score of key performance indicator, $KPI_{ij}$, which is determined by the performance indicator analyzer, with its weighting to determine the performance score related to an objective, $w_{ij}$, which is retrieved from the knowledge base. Moreover, constraints are included in the model. Constraints 3.4 and 3.6 specify that the weighting of objective and key performance indicator should be numeric values between 0 and 1, respectively. Constraints 3.5 and 3.7 require that the summation of all weighting of objectives and key performance indicators should be equal to 1.

*(iii) Performance Evaluation Model*  

The performance evaluation model is employed to evaluate the resource allocation decision’s overall performance score and present the performance results along with suggestions for improvements. It adopts the CBR method to retrieve past cases for supporting performance evaluation. The objectives for performance measurement and specifications of resource allocation are case attributes utilized to browse and retrieve relevant cases from the case library. After generating a list of cases based on the degree of similarity, their overall performance scores can be compared with the new case to assess whether the current resource allocation decision is correct. Any new approach will then be identified to improve the performance level. If the performance of the current case is poorer than that of past
cases, the resource allocation decisions in those past cases can serve as useful suggestions for the staff to reallocate the resources effectively. Subsequently, a manufacturing plan can be generated to present the results of, and recommendations for, the performance while the new case is retained in the case library.

The design steps of CBR methods/techniques in this model are discussed as follows:

*Step 1: Define the CBR’s basic mechanism*

CBR is one of the emerging paradigms for designing intelligent systems. According to Kolondner (1993), the problem-solving life cycle in a CBR consists of the following four steps as illustrated in Figure 3.8 (extracted from Kolondner, 1993): (i) retrieve the most similar case(s) to the new case; (ii) adopt or reuse information and knowledge in the retrieved case to solve the new case; (iii) revise the proposed solution — a feedback mechanism is included in CBR systems to diagnose the solution in the case; and (iv) retain the experience/cases that are likely to be useful for future problem-solving. The new case will be saved in the case/knowledge repository for future application.

![Figure 3.8 A CBR Cycle (Extracted from Kolondner, 1993)](image-url)
Step 2: Define the case attributes for representing the case

According to Liao et al. (2000), case representation can assume different kinds of forms, such as topological structure, tree structure, relational scheme, attributes-values pairs, frames, objects, predicates, and semantic rules. Case representation identifies and represents a case’s characteristics in both problem description and solution. Based on the case retrieval method, the format of case representation is different. Usually, the case’s content consists of more than one attribute so that the case can be more easily recovered during the case retrieval process. The performance evaluation model’s case attributes are described in Table 3.3.

<table>
<thead>
<tr>
<th>Item</th>
<th>Data type</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company objective</td>
<td>Text</td>
<td>customization, cost reduction, innovation</td>
</tr>
<tr>
<td>Maintenance strategy</td>
<td>Text</td>
<td>preventive, corrective, time-based</td>
</tr>
<tr>
<td>Customer</td>
<td>Text</td>
<td>customer name/code</td>
</tr>
<tr>
<td>Product type</td>
<td>Text</td>
<td>product name/code</td>
</tr>
<tr>
<td>Product size</td>
<td>Text</td>
<td>small, medium, large, extra large</td>
</tr>
<tr>
<td>Product quantity</td>
<td>Number</td>
<td>number of pieces</td>
</tr>
</tbody>
</table>

Step 3: Define the case retrieval method

According to Aamodt and Plaza (1994), the basic function of case retrieval is to retrieve old cases stored in the case library. The case retrieval process consists of subtasks, referred to as identify features, initial match, search, and select. From the review studies of knowledge-based system development, three case indexing mechanisms, including inductive indexing, k-nearest neighbor, and knowledge guide are widely applied to retrieve the case. Among them, the k-nearest neighbor is the most well-known case indexing method widely adopted in various domains. The nearest neighbor method is employed for determining the input case's similarity to
the retrieved cases. The similarity of each case attribute from the input and retrieved case is found and multiplied by a pre-determined weighting factor. The similarity ratio is then calculated by summing up the similarity of all attributes, as demonstrated by \textbf{Equation 3.8}.

$$\sum_{i=1}^{n} w_i \times \text{sim}(f_i^I, f_i^R)$$

(3.8)

where

- $w_i$ = weight of feature $i$
- $\text{sim}$ = similarity function
- $f_i^I, f_i^R$ = values of feature $i$ in the input case and retrieved case

Based on the degree of similarity, a list of ranked cases is generated to provide suggestion and knowledge for system users.

\textit{Step 4: Define a case content in the knowledge repository}

According to Kolodner (1991), a case comprises (1) the problem that describes the state of the world when the case occurred, (2) the solution which states the derived solution to that problem, and (3) the outcome which describes the state of the world after the case occurred. A case can be represented in a variety of forms in using the full range of AI representational formalisms, including literal, character, integer, and symbol. In the case base, each case is composed of three parts: case number, problem description, and recommended solution. The case number is assigned by the knowledge-based engine to provide a unique identification to the case in the repository. The problem description contains the case attributes that represent the specifications of the customer orders in the case. These case attributes are used to
match with the input case’s attributes for retrieving useful cases. The recommended solution is the suggested performance indicators, operations workflow, production machine, and maintenance policy plan that solves the problem. The knowledge sources are perceived as any potential malfunctions, errors, or problems. Recommendations on handling the situations are provided to the staff.

3.4.2 Machine Flexibility Assessor

The machine flexibility assessor’s main function is to minimize the mental loading of production planner for handling the machine breakdown problem on the production floor. Here, machine flexibility (MF) considers the machines’ characteristics in processing a specific operation. The machine flexibility assessor is constructed by a mathematical model for MF calculation. The MF’s result serves as an important index to support different business applications, including resource allocation, machine scheduling, maintenance policy assessment, and emergent order handling.

A mathematical model is developed to measure the MF by integrating three essential performance attributes within a production system: machine availability, quality of product, and production rate. The dynamic aspects of the machine such as efficiency and production quality to perform certain product items are captured and defined by the data manipulation framework discussed in Section 4.4.3. Unlike the existing MF models that are mentioned in Chapter 2, the proposed model enables manufacturers to define the probability of transferring a specific product operation from one machine to another machine in real time. The proposed result provides an updated and accurate flexibility measurement of each machine according to three performance attributes and set up effectiveness when performing certain product items. The model is described as follows.
Consider a production system that has a number of machines \( (1\ldots m) \), which can manufacture a number of product \( (1\ldots \alpha) \). The elements of MF are defined to include the machine capability \( (Q_{m\alpha}) \) and set up effectiveness \( (\rho_{m\alpha}) \). The MF of machine \( m \) for producing product \( \alpha \) is obtained by Equation 3.9.

\[
\phi_{m\alpha} = \omega_1 \phi_{m\alpha} + \omega_2 \rho_{m\alpha}
\]

(3.9)

where \( \omega_1, \omega_2 \) are the weighting factors of MF, \( \omega_1 + \omega_2 = 1 \) and \( 0 \leq \phi_{m\alpha} \leq 1 \).

For the machine capability \( (Q_{m\alpha}) \), each machine is considered to possess its production rate \( (r_{m\alpha}) \), quality \( (q_{m\alpha}) \), and machine availability \( (t_m) \) for producing a product item \( \alpha \). The specification of the above value is collected and recorded at the KPMS’ first module. The production capability of machine \( m \) for producing a product item \( \alpha \) is calculated by Equation 3.10.

\[
Q_{m\alpha} = r_{m\alpha} q_{m\alpha} t_m
\]

(3.10)

while the relative production capability of machine \( m \) is determined by Equation 3.11.

\[
\phi_{m\alpha} = \frac{Q_{m\alpha} \delta_{m\alpha}}{Z_{\alpha}^\phi}
\]

(3.11)

where a binary variable is defined as

\[
\delta_{m\alpha} = \begin{cases} 
1 & \text{if production of } \alpha \text{ is allowed} \\
0 & \text{elsewhere}
\end{cases}
\]

and

\[
Z_{\alpha}^\phi = \sum_{m \in M} Q_{m\alpha}
\]

(3.12)

\( \phi_{m\alpha} \) is a normalized index of machine \( m \)'s capability for producing product \( \alpha \).

For the setup effectiveness of machine \( (\rho_{m\alpha}) \), the setup time is considered as \( S_{m\alpha} \), and the setup effectiveness is determined by Equation 3.13.
\[
\rho_{m\alpha} = \frac{\max (S_{m\alpha} | \alpha) + \min (S_{m\alpha} | \alpha) - S_{m\alpha}}{Z_{\alpha}^\rho} \tag{3.13}
\]

where

\[
Z_{\alpha}^\rho = \sum_{m \in M} \delta_{m\alpha} \left( \max (S_{m\alpha} | \alpha) + \min (S_{m\alpha} | \alpha) - S_{m\alpha} \right) \tag{3.14}
\]

In a flexible production system, an operation can be performed by more than one machine, having considered that different machines may not possess the same capability and setup effectiveness. Therefore, the assignment of an operation to a machine can be ranked according to its real-time machine capability and setup effectiveness. Thus, the change of relative MF from one machine \( m \) to another machine \( x \) for producing product \( \alpha \) can be presented in Equation 3.15:

\[
\{ RMF_{m\alpha} \} = \Phi_{\alpha} = \begin{pmatrix} \Phi_{1\alpha} & \cdots & \Phi_{M\alpha} \\ \vdots & \ddots & \vdots \\ \Phi_{M1\alpha} & \cdots & \Phi_{MM\alpha} \end{pmatrix} = \begin{pmatrix} \delta_{11\alpha} & \frac{\phi_{21\alpha}}{\phi_{2\alpha}} & \delta_{12\alpha} & \cdots & \frac{\phi_{M1\alpha}}{\phi_{M\alpha}} & \delta_{1M\alpha} \\ \frac{\phi_{21\alpha}}{\phi_{2\alpha}} & \delta_{22\alpha} & \cdots & \frac{\phi_{M2\alpha}}{\phi_{M\alpha}} & \delta_{2M\alpha} \\ \vdots & \ddots & \ddots & \vdots & \vdots \\ \frac{\phi_{M1\alpha}}{\phi_{M\alpha}} & \delta_{M1\alpha} & \cdots & \delta_{M2\alpha} & \cdots & \delta_{MM\alpha} \end{pmatrix} \tag{3.15}
\]

By using Equation 3.13, the impact of change can be assessed when shifting from one machine to another one. This index value is important for the production planner to determine the right machine for handling the emergent order or machine breakdown problem.

### 3.5 Summary

The two module architectures of the proposed KPMS and the technology adoption of two modules were described in the previous sections. The proposed system’s knowledge manipulation and flexibility assessment functions enable production planners to achieve the productivity improvement and resource
performance assessment focusing on asset management perspective. The details of the validation and application of the proposed system are discussed in the case study, with a helmet manufacturing company as an example in Chapter 4.
Chapter 4 System Implementation and Case Study

4.1 Introduction

Given the importance of efficiency enhancement on the production floor, manufacturers are driven to formulate a number of planning decisions regarding resource allocation, performance measuring indicators setup, maintenance policy, and machine selection. Further, to ensure that the production floor’s flexibility is increased to cope with any emergent dilemmas such as machine breakdown in the midst of production, manufacturers should be aided with a decision support system to conduct machine flexibility assessment on the floor. To validate the feasibility of adopting KPMS in providing reliable knowledge-based decision support, an industrial application case study has been conducted in a helmet manufacturing company. This chapter provides a profile of the company, its existing practices and operations, and the KPMS roadmap.

4.2 Case Study in a Manufacturing Company (YeeFung Polyfoam Limited)

In the manufacturing industry, many companies adopt the make-to-order (MTO) strategy to create customized products for customers. To fulfill orders with a short lead time, it is critical to monitor manufacturing activities and fully utilize production resources by scheduling these activities. Moreover, because production resources such as machines, equipment, and shop floors are limited, immediate actions should be carried out to settle any emergent events that may disrupt the production process. Examples of such events are machine breakdown, scheduled maintenance activities, lack of raw materials, and change in customer demand.

YeeFung Polyfoam Limited is one of the largest manufacturers of sports helmets, serving a significant number of top brands in the United States and Europe such as
Bell, Giro and Lazer. It was established in 1976 and currently has five factories in South China. It is an original equipment manufacturer (OEM) creating products based on customers’ requirements. Its products include road helmets, snow helmets, bike helmets, and motor helmets made of various materials such as expandable polystyrene (EPS), expandable polyethylene (EPP), and fiberglass. Figure 4.1 shows the sports helmets that are manufactured by YeeFung Polyfoam Limited. Figure 4.2 illustrates the standard manufacturing process involved in producing EPS sports helmets.

Figure 4.1 Sports Helmets Manufactured by YeeFung Polyfoam Limited

Figure 4.2 Standard Manufacturing Process for Sports Helmets
4.3 Problem Definition of YeeFung Polyfoam Limited

At present, YeeFung Polyfoam Limited leverages the ERP system to support production planning decisions. However, the ERP system is data-driven rather than knowledge-driven, merely providing manufacturing or purchasing data or information. As a manufacturer, the company relies on experience to support decision-making for the production plan for a wide range of products. Further, YeeFung Polyfoam Limited serves different groups of customers with unique production requirements and workflows. Owing to factors such as seasonality and production life cycle, product flow within the production shop floor changes dynamically.

Constrained by limited resource/machine capability, decisions must be formulated carefully, giving due regard to ways of fully utilizing the resource/machine while keeping them within a steady productivity level without fear of breakdown. When faced with customers’ increasing production demand, this issue further intensifies the challenges faced by the manufacturer during production planning if only the current ERP system is employed. Therefore, YeeFung Polyfoam Limited seeks to improve the production floor in the following aspects:

- A systematic approach to support knowledge for manufacturers during production planning and performance measurement
- A real-time production shop floor control for managing the flow of WIP, finished goods, and machine operations status checking
- A dynamic machine flexibility assessment for handling emergent issues on the production floor

4.4 KPMS Implementation in YeeFung Polyfoam Limited

KPMS is implemented on YeeFung Polyfoam Limited’s production shop floor
to facilitate the decision-making process involved in production planning and machine flexibility assessment. The system framework is founded on the Microsoft Visual Basic platform, together with RFID and sensor built for real-time resource location tracking and machine production capability assessment.

Before KPMS implementation in YeeFung Polyfoam Limited, several physical setups are required. The system deployment comprises four core areas, namely, RFID system setup for data capture, sensor installation for data capture, data manipulation framework in the data warehouse, and determination of KPI content to support knowledge creation.

4.4.1 The RFID System’s Physical Setup on the Production Shop Floor

YeeFung Polyfoam Limited’s RFID system infrastructure should include RFID tags attached to appropriate positions on the helmets and RFID readers with antennas installed in selected machine cells, shop floors, and warehouses. In current stage, YeeFung Polyfoam Limited has attached RFID tags to the physical asset of helmets only. It may attach RFID tags to other products (e.g. bumper system) and assets in future.

Figure 4.3 displays the manufacturing process flow of helmet production. As a WIP helmet is primarily formed in the injection molding process, RFID tracking is implemented in this process and its subsequent shop floors and warehouses. As shown in Figure 4.4, RFID tags are attached to the inner surface of each WIP helmet during the injection molding process. In order to track the location of RFID-tagged helmets during the manufacturing process, RFID readers and antennas are set up in the portals of the following four production shop floors and two warehouses:

- Injection mold shop floor
- Paint spray shop floor
- Decal stick shop floor
- Assembly shop floor
- WIP goods warehouse
- Finished goods warehouse

Figure 4.3 Manufacturing Process Flow of Helmet Production

Figure 4.4 (a) The Staff Sticks the RFID Tag on a WIP Helmet (b) A RFID-tagged Helmet
To conduct this, various site tests covering orientation and height tests are required. To study the RFID gateway’s site performance, the RFID Deployment Optimizer (RFID-DO), a software package based on a patent in benchmarking and deployment-optimization method developed by Kwok et al. (2007), is utilized to conduct the required tests in measuring, evaluating, and optimizing RFID applications in the deployment process.

(i) **Orientation test**

The orientation test is conducted to determine the suitable orientation of locating the tag on the helmet within different read ranges. As illustrated in Figure 4.5, it compares the performance of the horizontally and vertically located tags on the helmet when being read by the antenna. The test is repeated by setting the antenna at different distances from the tracking object, ranging from 2 m to 4 m.

As illustrated in Figure 4.6, results reveal that the tagged helmets with both vertical and horizontal orientations are well detected (over 90%) within nearly any distance between the antenna and object. However, the horizontal orientation’s tag performance drops dramatically at a distance of 4 m. Therefore, vertical orientation should be selected to locate the tag on the helmet, while the distance between the
antenna and object should be pegged below 3.8 m.

Figure 4.6 Results of Orientation Test

(ii) Height test

The height test is conducted to determine the suitable height for the tagged WIP helmets and ensure that it will be read by the antenna. As the tagged WIP helmets are placed in a polystyrene box and stacked on the material handling equipment during transfer as shown in Figure 4.7, the test compares the reading performance of tags located within different heights. The height test's setup is presented in Figure 4.8.

Figure 4.7 (a) WIP Helmets Placed in a Polystyrene Box (b) The Polystyrene Boxes With WIP Helmets Are Stacked on the Material Handling Equipment
Eight boxes containing the tagged helmets are stacked on one column and read by the antenna situated at a specified distance. The test is repeated by setting the antenna at different distances, ranging from 2 m to 3.4 m, from the boxes.

![Figure 4.8 (a) Setup of Height Test (b) Tagged Helmet Was Put Inside the Polystyrene Box](image)

![Figure 4.9 Results of Height Test](image)
As illustrated in Figure 4.9, the test results reveal that all tagged helmets located between the first and seventh rows of boxes can be read satisfactorily within distances ranging from 2 m to 3 m. However, the reading performance of the tagged helmet located at the eighth row is relatively poor. Thus, a maximum of seven boxes should be utilized to store the tagged helmets and stacked when being transferred across different shop floors and warehouses.

(iii) Tag performance on different types of helmets

To ensure that RFID tags can be read from different products, a test is conducted to study the tag performance on different types of helmets such as snow helmet, road helmet, and high-end road helmet, which are shown in Figure 4.10. As illustrated in Figure 4.11, the antennas are set at different distances from the RFID-tagged helmet which is put on a wooden box, ranging from 2 m to 3.6 m. RFID-DO program is adopted to compare the reading performance of the tagged products. It sends and receives signals from the antennas for ten times in which each time lasts for 10 seconds. Then, ten sets of data related to the percentage of successful reads are collected. Among them, the best and the worst data results are neglected to reduce the error while the average of the remaining data sets is calculated. The test results generated by RFID-DO are presented in Table 4.1. As shown in Figure 4.12, all types of testing products can be well detected over 90% from 2 m to 2.8 m. However, there is a drop of reading performance after 3 m.
Figure 4.11 (a) Setup of Tag Performance Test (b) RFID-Tagged helmet

Table 4.1 The Test Results Generated by RFID-DO (1 represents the best performance and 0 represents the worst performance)

<table>
<thead>
<tr>
<th>Testing products</th>
<th>Distance between antennas and products (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.0</td>
</tr>
<tr>
<td>Alien tag</td>
<td>1.000</td>
</tr>
<tr>
<td>Snow helmet</td>
<td>1.000</td>
</tr>
<tr>
<td>Road helmet</td>
<td>1.000</td>
</tr>
<tr>
<td>High-end road helmet A</td>
<td>1.000</td>
</tr>
<tr>
<td>High-end road helmet B</td>
<td>1.000</td>
</tr>
</tbody>
</table>

After site tests are conducted, RFID gateways including the readers and antennas are installed on production machine cells and in the portals of shop floors and warehouses, as illustrated in Figure 4.13. To monitor production status and assess manufacturing flexibility, an RFID tag is attached to each WIP helmet, to be read by the RFID reader when sent to different machines, shop floors, and warehouses.
As shown in Figure 4.14, the RFID-tagged WIP helmets are transferred through an RFID gateway. An RFID middleware is utilized to process the transmission of information between reader and system. It filters the signals collected by the RFID devices and records the tag ID, reader ID, and time when an RFID-tagged WIP helmet is detected in the gateway. An example of data collected by RFID devices is presented in Figure 4.15.
In order to study the reading rate of tagged WIP helmets, different numbers of polystyrene boxes containing the tagged WIP helmets are placed on the material handling equipment, which are passed through the RFID gateway. The reading rate of the tagged WIP helmets when they are passed through the RFID gateway is shown in Figure 4.16. It shows that the reading rate is over 92%, which is satisfactory to
fulfill the need of identifying the WIP helmets that are being transferred. For the missing items, less than 8%, it can be complemented with data in the ERP system of the company.

By applying RFID technology, the WIP helmets’ location is tracked by the system in real time. Moreover, it identifies the types of WIP helmets being processed to assist in determining machine flexibility.

4.4.2 Sensor Installation for Data Capture

In the proposed system, one of the main functions is to measure relative machine flexibility. To achieve this, the operating status of a machine, which processes a certain product item, should be accurately recorded. In the case of YeeFung Polyfoam Limited, the injection molding machine’s operating status should be monitored, because injection molding is a critical process in helmet manufacturing. The machine is equipped with a gate which can be opened for placing
the molds. To measure the injection molding machine’s operating status, the gate’s on/off status can be detected by a limit switch, as illustrated in Figure 4.17. The switch is used to record the frequency and cycle time of manufacturing operations run by the injection molding machine in processing a particular product. By doing so, each injection molding machine’s daily throughput and operating time are accurately recorded and stored in the database. Further, a temperature sensor is inserted into the machine. It records the shop floor’s temperature to prevent overheating.

![Figure 4.17 Sensors’ Installation in an Injection Molding Machine](image)

As illustrated in Figures 4.18 and 4.19, a device is connected with the sensors to convert the received signals into machine status data, which can be transferred to a computer through port setting. Table 4.2 presents the data captured from the sensors in recording an injection molding machine’s operating status during production on May 8, 2008. Data on the machine gate’s operating status and temperature are
captured by the limit switch and temperature sensor, respectively. Time stamps are recorded as well.

![Figure 4.18 Device Connected with Sensors For Data Capture](image)

**Figure 4.18 Device Connected with Sensors For Data Capture**

![Figure 4.19 Transfer of Data Captured by Sensors to Computer](image)

**Figure 4.19 Transfer of Data Captured by Sensors to Computer**
Table 4.2 The Operating Status of an Injection Molding Machine on 5/8/2008

<table>
<thead>
<tr>
<th>ID</th>
<th>Date</th>
<th>Time</th>
<th>Status of machine gate</th>
<th>Temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>5/8/2008</td>
<td>15:56:14</td>
<td>0</td>
<td>32</td>
</tr>
<tr>
<td>17</td>
<td>5/8/2008</td>
<td>16:00:03</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>18</td>
<td>5/8/2008</td>
<td>16:03:42</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>19</td>
<td>5/8/2008</td>
<td>16:07:22</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>20</td>
<td>5/8/2008</td>
<td>16:11:01</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>21</td>
<td>5/8/2008</td>
<td>16:14:45</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>22</td>
<td>5/8/2008</td>
<td>16:22:49</td>
<td>0</td>
<td>31</td>
</tr>
<tr>
<td>23</td>
<td>5/8/2008</td>
<td>16:26:37</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>24</td>
<td>5/8/2008</td>
<td>16:30:12</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>25</td>
<td>5/8/2008</td>
<td>16:33:56</td>
<td>1</td>
<td>29</td>
</tr>
<tr>
<td>26</td>
<td>5/8/2008</td>
<td>16:37:35</td>
<td>0</td>
<td>31</td>
</tr>
<tr>
<td>27</td>
<td>5/8/2008</td>
<td>16:41:16</td>
<td>1</td>
<td>29</td>
</tr>
<tr>
<td>28</td>
<td>5/8/2008</td>
<td>16:44:55</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>30</td>
<td>5/8/2008</td>
<td>16:52:31</td>
<td>0</td>
<td>30</td>
</tr>
</tbody>
</table>

There are two types of machine gate status: the machine gate is closed and it leaves the limit switch, which is represented by a value of 0, and the machine gate is open and it hits the limit switch, which is represented by a value of 1. The former indicates that the injection molding process starts once the gate is closed, while the latter indicates that the injection molding process finishes once the gate is again open. On the other hand, the shop floor’s temperature during the operation is recorded in degree Celsius.

4.4.3 The Data Manipulation Framework in the Data Warehouse

This data manipulation framework consists of two databases for storing data captured from RFID and sensor for calculating MF in the K-PM module. One of the main performance indicators in MF is the machines’ operation efficiency in processing a product item within a certain time period. To define this indicator, it is
essential to incorporate two kinds of data captured by RFID and sensor technologies.

In the previous section, the RFID system, which helps in identifying the entry time of each product item to different machine cells, was clearly defined. Further, since the machine is embedded with a sensor, the start and end of each product item’s processing time is defined as well. Thus, by incorporating these RFID data with sensor data, the data manipulation framework combines these data and represents each machine’s operating status for processing a specific product item at certain time period. Figure 4.20 presents an example of the measurement of machine efficiency in processing a product item by integrating data collected from RFID and sensor.

4.4.4 Determine KPIs’ Content to Support Knowledge Creation

A knowledge repository in the proposed system stores knowledge on the selection of performance indicators for different helmets’ production. In the previous
part, a data manipulation framework demonstrated the incorporation of RFID and sensor data to represent each machine’s operating status for processing a specific product item at certain time period. Similarly, in other KPIs that are represented, the dimension of quality, cost, and production efficiency are obtained in the same manner. Thus, the KPIs’ content for performing certain product items are defined and utilized for the content of knowledge rules described in Section 3.4.1. The KPIs’ calculation formula for different measurement is presented in Table 4.3.

Table 4.3 The KPI Measurement Formula

<table>
<thead>
<tr>
<th>Performance measures</th>
<th>Performance indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Performance indicators</strong></td>
</tr>
<tr>
<td>Equipment</td>
<td></td>
</tr>
<tr>
<td>Availability</td>
<td>( \frac{\text{Scheduled time} - \text{All downtime}}{\text{Scheduled time}} )</td>
</tr>
<tr>
<td>Product rate</td>
<td>( \frac{\text{Average production rate}}{\text{Highest achieved production}} )</td>
</tr>
<tr>
<td>Overall equipment effectiveness (OEE)</td>
<td>( \text{Availability} \times \text{Product rate} \times \text{Quality rate} )</td>
</tr>
<tr>
<td>Reliability</td>
<td>( \frac{\text{Total operating time}}{\text{Number of failures}} )</td>
</tr>
<tr>
<td>Process</td>
<td></td>
</tr>
<tr>
<td>Schedule compliance</td>
<td>( \frac{\text{Work completed as scheduled}}{\text{Total work scheduled}} )</td>
</tr>
<tr>
<td>Production cycle time</td>
<td>( \frac{\text{Actual production time} - \text{target lead time}}{\text{Target lead time}} )</td>
</tr>
<tr>
<td>Quality</td>
<td></td>
</tr>
<tr>
<td>First pass yield</td>
<td>( \frac{\text{Number of in conformity items}}{\text{Total production}} )</td>
</tr>
<tr>
<td>Defect rate</td>
<td>( \frac{\text{Number of defect items}}{\text{Total production}} )</td>
</tr>
<tr>
<td>Scrap rate</td>
<td>( \frac{\text{Scrapped production}}{\text{Total production}} )</td>
</tr>
</tbody>
</table>

On the other hand, KPIs related to machines’ production capability are found by analyzing the data collected from sensors, which are embedded on machines. For example, Figure 4.21 presents the average hourly throughput of a machine in the
Chapter 4 System Implementation and Case Study

week of 5/8/2008. Figure 4.22 shows the cycle time of an injection molding machine which was collected on 5/8/2008 while Figure 4.23 illustrates the throughput of the machine at different working hours.

Figure 4.21 Average Hourly Throughput of a Machine in the Week of 5/8/2008

Figure 4.22 Cycle Time of Injection Molding Machine Collected on 5/8/2008
Figure 4.23 Throughput of a Machine at Different Working Hours

### 4.5 KPMS’ Operations Mechanism in the Decision Support for Production Planning

Figure 4.24 illustrates KPMS’ operating procedures in formulating a manufacturing plan. There are five steps in KPMS operations, starting from retrieval of relevant attributes to the retention of useful cases.

**Step 1: Select the KPIs**

Figure 4.25 illustrates KPMS’ user input interface for YeeFung Polyfoam Limited. By selecting appropriate buttons, the user interface input includes manufacturing strategy, asset management policy, customer name, product type, product model, color, size, and production quantity. This information represents the production requirements for certain product items. After entering the above information by clicking the “submit” button, the KPMS begins to retrieve relevant case attributes for executing the knowledge retrieval’s system function for production planning.
According to product specification, the KPMS’ performance indicator analyzer recalls knowledge (in the form of rules) from the repository. The performance indicator analyzer employs a rule-based reasoning technique to define a list of KPIs, which represent part of the case attributes for knowledge retrieval purposes. Each KPI possesses different weighting to represent its importance to the specific production case. Therefore, the weighting assignment should be conducted by a certain systematic method. In this study, analytical hierarchy process (AHP) is
adopted and the weight assignment is revealed in Step 2.

Figure 4.25 User Input Interface of KPMS for YeeFung Polyfoam Limited

**Step 2: Define the weight of KPIs (attribute values)**

In this study, KPIs’ categories are generally divided into cost, quality, time, flexibility, and asset reliability. The weighting value of each category differs according to each product specification. Therefore, the production manager is required to enter the level of importance to justify it. As demonstrated in Table 4.4, Saaty’s 1–9 scale for AHP preference is tapped to rate each category’s importance level.

The production manager first enters each category’s rate. Through the pairwise comparison method, each category’s rate is displayed in Table 4.5. Each category’s corresponding weight value is defined and presented in the ninth column of Table 4.6. The KPIs that belong to the specific category will be assigned with a specific category's corresponding weighting value.
**Table 4.4 Saaty’s 1–9 Scale for AHP Preference**

<table>
<thead>
<tr>
<th>Verbal judgment of preference</th>
<th>Numerical rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equal importance</td>
<td>1</td>
</tr>
<tr>
<td>Weak importance of one over another</td>
<td>3</td>
</tr>
<tr>
<td>Essential or strong importance</td>
<td>5</td>
</tr>
<tr>
<td>Demonstrated importance</td>
<td>7</td>
</tr>
<tr>
<td>Absolute importance</td>
<td>9</td>
</tr>
<tr>
<td>Intermediate values between the two adjacent judgments</td>
<td>2, 4, 6, 8</td>
</tr>
<tr>
<td>If activity $i$ has one of the above numbers assigned to it when compared with activity $j$, then $j$ has the reciprocal value when compared with $i$</td>
<td>Reciprocal of above numbers</td>
</tr>
</tbody>
</table>

Source: Saaty and Alexander, 1981

**Table 4.5 Each Category’s Level of Importance**

<table>
<thead>
<tr>
<th>Pairwise comparison between each category</th>
<th>Cost</th>
<th>Quality</th>
<th>Time</th>
<th>Delivery</th>
<th>Flexibility</th>
<th>Asset reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>1</td>
<td>1/5</td>
<td>1/3</td>
<td>4</td>
<td>7</td>
<td>1/3</td>
</tr>
<tr>
<td>Quality</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>6</td>
<td>3</td>
<td>1/5</td>
</tr>
<tr>
<td>Time</td>
<td>3</td>
<td>1/7</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>1/2</td>
</tr>
<tr>
<td>Delivery</td>
<td>1/4</td>
<td>1/6</td>
<td>1/3</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Flexibility</td>
<td>1/7</td>
<td>1/3</td>
<td>1/3</td>
<td>1/2</td>
<td>1</td>
<td>1/5</td>
</tr>
<tr>
<td>Asset reliability</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>1/3</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 4.6 Corresponding Weighting Value of Each Category**

<table>
<thead>
<tr>
<th>Weight value of each category</th>
<th>Cost</th>
<th>Quality</th>
<th>Time</th>
<th>Delivery</th>
<th>Flexibility</th>
<th>Asset reliability</th>
<th>Average</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost</td>
<td>0.08</td>
<td>0.029</td>
<td>0.03</td>
<td>0.269</td>
<td>0.333</td>
<td>0.063</td>
<td>0.134</td>
<td>13.45%</td>
</tr>
<tr>
<td>Quality</td>
<td>0.403</td>
<td>0.146</td>
<td>0.636</td>
<td>0.404</td>
<td>0.142</td>
<td>0.038</td>
<td>0.295</td>
<td>29.53%</td>
</tr>
<tr>
<td>Time</td>
<td>0.242</td>
<td>0.02</td>
<td>0.09</td>
<td>0.202</td>
<td>0.142</td>
<td>0.095</td>
<td>0.132</td>
<td>13.24%</td>
</tr>
<tr>
<td>Delivery</td>
<td>0.02</td>
<td>0.024</td>
<td>0.03</td>
<td>0.067</td>
<td>0.095</td>
<td>0.573</td>
<td>0.135</td>
<td>13.51%</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.011</td>
<td>0.048</td>
<td>0.03</td>
<td>0.033</td>
<td>0.047</td>
<td>0.038</td>
<td>0.035</td>
<td>3.50%</td>
</tr>
<tr>
<td>Asset reliability</td>
<td>0.242</td>
<td>0.73</td>
<td>0.181</td>
<td>0.022</td>
<td>0.238</td>
<td>0.191</td>
<td>0.267</td>
<td>26.77%</td>
</tr>
</tbody>
</table>
Step 3: Retrieve and compare cases

Each case in the case repository contains case attributes and recommended solutions. Case attributes involve company objectives and customer order descriptions such as customer name, product type, size and quantity while recommended solutions include process flow, resources allocation and key performance indicators. The cases are captured by collecting production order documents from various production shop floors and capturing the domain knowledge from production supervisors and staff. Around 120 cases were involved in the case study company. The case retrieval process is conducted through performance evaluation module using the nearest neighbor algorithm. Based on the input case’s attribute values, the KPMS compares each case’s similarity within the knowledge repository. Table 4.7 presents an example of an input case and a historical case (Case 002) comparison. For the case attributes, it consists of product information, manufacturing strategy, and KPIs. The weighting value of each KPI is defined based on the results of Table 4.6, while the other case attribute’s weighting value is defined by the production manager. The weighting values identify the importance of attribute to the case, and such weighting values are likewise employed for the input case and historical case’s similarity measurement for the next step.

Step 4: Rank similar cases

In this step, the similarity value between the input case and retrieved case 002 in Table 4.7 is calculated by the nearest neighbor algorithm to rank cases in a descending order. To facilitate understanding, calculation for the similarity value, which is shown in Equation 3.8, between input case and historical case 002’s attribute-reliability is illustrated as follows:
Similarity value between input case and historical case 002

\[ w(\text{Reliability}) \cdot \left( \text{sim}(\text{case}_{\text{input}}(\text{Reliability}), \text{case}_{002}(\text{Reliability})) \right) \]

\[ = 0.27 \cdot (0.85 - 1) \]

\[ = 0.041 \]

By summing up all case attributes, the overall similarity value between input case and historical case 002 is calculated, and the result is 38.46%. Likewise, the similarity values between the input case and other cases within the knowledge repository are calculated in the same way.

<table>
<thead>
<tr>
<th>Case Attributes</th>
<th>Category</th>
<th>Weight of features</th>
<th>Input case</th>
<th>Case 002</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing strategy</td>
<td>Strategy</td>
<td>0.3</td>
<td>Customization</td>
<td>Customization</td>
</tr>
<tr>
<td>Asset management policy</td>
<td>Strategy</td>
<td>0.2</td>
<td>Time-based</td>
<td>Time-based</td>
</tr>
<tr>
<td>Product type</td>
<td>Product</td>
<td>0.2</td>
<td>Bike helmet</td>
<td>Motorcycle helmet</td>
</tr>
<tr>
<td>Model</td>
<td>Product</td>
<td>0.1</td>
<td>BH1082</td>
<td>MH0011</td>
</tr>
<tr>
<td>Color</td>
<td>Product</td>
<td>0.1</td>
<td>Black</td>
<td>Blue</td>
</tr>
<tr>
<td>Size</td>
<td>Product</td>
<td>0.1</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>On time shipment</td>
<td>KPIs-Delivery</td>
<td>0.13</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Reliability</td>
<td>KPIs-Reliability</td>
<td>0.27</td>
<td>85%</td>
<td>100%</td>
</tr>
<tr>
<td>Cycle time</td>
<td>KPIs-Time</td>
<td>0.13</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>Defect rate</td>
<td>KPIs-Quality</td>
<td>0.29</td>
<td>0.1</td>
<td>0.15</td>
</tr>
<tr>
<td>Production cost</td>
<td>KPIs-Cost</td>
<td>0.13</td>
<td>2.5</td>
<td>3</td>
</tr>
</tbody>
</table>

**Figure 4.26** illustrates eight cases with descending similarity value. Among these cases, case “009” demonstrates the highest similarity value (64.1%), which is obtained to support production planning.
Step 5: Revise and retain the “retrieved case”

This step decides whether case adaptation should be applied. Based on the results of Step 4, strategy planners can select the case with the highest similarity value in Step 4 to create a production plan for the new product item. The case will be revised by adopting production process workflows and other issues, including the KPIs setup and machine selection. Based on the new product specifications, the retrieved process flow case is modified by adding new steps or trimming unnecessary workflow. Once the workflow is modified, relevant parameters such as workforce and facilities are adjusted accordingly.

Figure 4.26 The Retrieved Case Results of the KPMS

Workflow pertains to important information which provides guidance to workers and supports the production manager in machine scheduling. Based on the new process workflow, the manpower and facility demand are calculated. Subsequently, KPIs for this new process workflow are defined.
Lastly, the resource allocation and machine consumption rate’s efficiency is recorded by the KPMS’ automatic data collection module. Once new case adaptation is completed, a new case is formed. A unique sequential case number is assigned automatically to this new case by the system. Thus, the new case is retained in the knowledge repository for future use.

4.6 KPMS’ Operations Mechanism in the Decision Support for Machine Flexibility Assessment

The core function of the KPMS’ machine flexibility assessor is to assess the impact of change when job is shifted from one machine to another. This index value allows the production planner to determine the right machine for handling the emergent order or machine breakdown problem. Figure 4.27 illustrates the machine flexibility assessor’s operating flow in selecting a machine for handling emergent cases on the production floor.

To facilitate understanding of the machine flexibility assessment model, a study of an injection machine selection for producing bike helmet AA002 is illustrated. In Yee Fung Company, an injection machine shop floor consists of eight injection molding machines for helmet injection molding operations. If machine 001, which has been selected to produce bike helmet AA002, is suddenly out of order, the production manager adopts the KPMS’ machine flexibility assessor to select another injection molding machine to produce the items without delay.

Step 1: Define each machine’s KPIs

In this step, the historical performance records of other remaining injection molding machines for producing bike helmet AA002 is retrieved from the data warehouse using the KPMS’ performance evaluation module. The historical
performance records, including KPIs of machine availability, product quality, and production rate, are retrieved. These performance records represent the machine’s capacity \( Q_{max} \) to produce bike helmet AA002 \( \alpha \). Meanwhile, setup effectiveness \( \rho_{max} \) is likewise retrieved in the same manner. The historical records reveal that only injection molding machines 003, 005, 006, 007, and 009 were utilized for the production of bike helmet AA002.

![Diagram](image)

**Figure 4.27 The Workflow of KPMS**

After defining these injection molding machines, the next step is to evaluate their real-time capacity. This is performed using the RFID technology to verify the WIP goods and sensor’s location to record each machine’s operational frequency. Real-time data is transmitted to the KPMS’ data warehouse, thereby reflecting the injection molding machines’ real-time operations status. Based on the retrieved data, injection molding machine 006 is fully loaded, while injection molding machines 003, 005, 007, and 009 possess enough capacity to handle extra production.
Step 2: Calculate each machine’s flexibility

According to the results in Step 1, four injection molding machines are currently capable of supporting the injection molding operations of AA002. During the selection process, relevant machine capability and setup effectiveness need to be defined to calculate machine flexibility. Table 4.8 presents these injection molding machines’ specifications when producing bike helmet AA002.

Table 4.8 The Specifications of Injection Molding Machines for Producing AA002

<table>
<thead>
<tr>
<th>Injection molding machine</th>
<th>Production rate ( r_m )</th>
<th>Quality rate ( q_m )</th>
<th>Machine availability ( \bar{T}_m )</th>
<th>Maximum Setup time ( \Delta T ) (min)</th>
<th>Minimum Setup time ( \Delta T ) (min)</th>
<th>Normal Setup time ( \overline{\Delta T} ) (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>001</td>
<td>0.95</td>
<td>0.7</td>
<td>0.3</td>
<td>45</td>
<td>25</td>
<td>33</td>
</tr>
<tr>
<td>003</td>
<td>0.87</td>
<td>0.9</td>
<td>0.2</td>
<td>35</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>005</td>
<td>0.9</td>
<td>0.75</td>
<td>0.1</td>
<td>40</td>
<td>19</td>
<td>32</td>
</tr>
<tr>
<td>007</td>
<td>0.88</td>
<td>0.85</td>
<td>0.15</td>
<td>43</td>
<td>23</td>
<td>35</td>
</tr>
<tr>
<td>009</td>
<td>0.86</td>
<td>0.93</td>
<td>0.23</td>
<td>42</td>
<td>20</td>
<td>29</td>
</tr>
</tbody>
</table>

The machine flexibility is calculated by Equation 3.9 in Section 3.4.2. In this case, weighting factors \( \omega_1, \omega_2 \) are assumed to be equal to 0.5, while production capacity \( \varphi_m \) and setup effectiveness \( \rho_m \) are defined using Equations 3.11 and 3.12 in Section 3.4.2 respectively. To facilitate understanding of machine flexibility calculation, injection molding machine 003 is tapped for demonstration.

The production capacity of machine (\( \varphi_3 \)) is

\[
\varphi_3 = \frac{Q_3 \Delta \varphi}{Z_3^{\rho}}, \quad (4.2)
\]

where

\[
Q_3 = r_3 q_3 \bar{T}_m = 0.87 \times 0.9 \times 0.2 = 0.156, \quad (4.3)
\]

and \( Z_3^{\rho} = 0.89 \). Therefore, \( \varphi_3 \) is \( 0.156 / 0.89 = 0.175 \).\( (4.4) \)

The setup effectiveness of machine (\( \rho_3 \)) is
Chapter 4 System Implementation and Case Study

\[ \rho_{3a} = \frac{\max (S_{3a} | \alpha) + \min (S_{3a} | \alpha) - S_{3a}}{Z_{3a}^0} \]  \quad (4.5)

where \[ \rho_{3a} = \frac{35 + 20 - 30}{151} = 0.165. \]  \quad (4.6)

After determining \( \varphi_{3a} \) and \( \rho_{3a} \), the machine flexibility of 003 is

\[ \phi_{3a} = \omega_1 \varphi_{3a} + \omega_2 \rho_{3a} = 0.5 (0.175) + 0.5 (0.165) = 0.258 \]  \quad (4.7)

By repeating the above calculations, the flexibility of machines 001, 003, 005, 007, and 009 for producing item AA002 is calculated and the results are presented in Table 4.9.

### Table 4.9 The Machine Flexibility among Five Injection Molding Machines

<table>
<thead>
<tr>
<th>Injection molding machine number</th>
<th>Machine flexibility</th>
<th>Value (0-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>001</td>
<td>( \phi_{3a} )</td>
<td>0.233</td>
</tr>
<tr>
<td>003</td>
<td>( \phi_{3a} )</td>
<td>0.258</td>
</tr>
<tr>
<td>005</td>
<td>( \phi_{3a} )</td>
<td>0.245</td>
</tr>
<tr>
<td>007</td>
<td>( \phi_{3a} )</td>
<td>0.342</td>
</tr>
<tr>
<td>009</td>
<td>( \phi_{3a} )</td>
<td>0.451</td>
</tr>
</tbody>
</table>

In a flexible production system, assigning an operation to a machine can be ranked according to its real-time machine capability and setup effectiveness. Thus, change of relative machine flexibility (\( RMF_{mca} \)) from machine 001 to other injection molding machines for producing bike helmet product \( \alpha \) can be presented using Equation 3.13 in Section 3.4.2.
Considering the breakdown case of machine 001, the RMF of machine 001 to other machines is presented in Table 4.10.

Table 4.10 The RMF from Machine 001 to Other Machines

<table>
<thead>
<tr>
<th>From Machine 001 to other machine number</th>
<th>RMF</th>
<th>Value</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>From 001 to 003</td>
<td>$\frac{\phi_{3a}\delta_{3a}}{\phi_{1a}}$</td>
<td>$0.258$</td>
<td>$0.233\delta_{3a}$</td>
</tr>
<tr>
<td>From 001 to 005</td>
<td>$\frac{\phi_{5a}\delta_{5a}}{\phi_{1a}}$</td>
<td>$0.245$</td>
<td>$0.233\delta_{5a}$</td>
</tr>
<tr>
<td>From 001 to 007</td>
<td>$\frac{\phi_{7a}\delta_{7a}}{\phi_{1a}}$</td>
<td>$0.342$</td>
<td>$0.233\delta_{7a}$</td>
</tr>
<tr>
<td>From 001 to 007</td>
<td>$\frac{\phi_{9a}\delta_{9a}}{\phi_{1a}}$</td>
<td>$0.451$</td>
<td>$0.233\delta_{9a}$</td>
</tr>
</tbody>
</table>

Step 3: Select the machine

After defining each injection molding machine’s RMF, the KPMS will then determine which machine is most suitable for producing bike helmet AA002. Because machine 007’s RMF is the largest compared with other machines’, injection molding machine 007 will then be selected to handle the emergent order of bike
helmet product AA002. With the help of KPMS, the production manager can speedily assess the impact of change when shifting a job order from one machine to another with the highest flexibility without compromising product quality rate and productivity rate. Thus, YeeFung Polyfoam Limited’s productivity is maintained through selecting the right machine with the highest flexibility on the production floor.
Chapter 5 Results and Discussion

5.1 Introduction

In this research, KPMS infrastructure has been designed for supporting decision-making processes of production planning and machine selection. It has been specifically designed for companies that encounter unpredictable problems on the production shop floor. KPMS has been implemented in a helmet manufacturing company to validate its feasibility in providing reliable decision support for production planners. In this chapter, the results and discussion of system implementation are presented. First, a comparison of the workflows between the conventional approach and the proposed KPMS approach is provided. Second, the results of implementing KPMS in YeeFung Polyfoam Limited are evaluated by quantitative measures. Third, the contributions of KPMS to manufacturing companies are discussed.

5.2 Comparison of the conventional approach and the proposed system

After the implementation of KPMS in YeeFung Polyfoam Limited, a workflow study is conducted in order to compare the differences between the conventional approach and the proposed KPMS approach in production management. Figures 5.1 and 5.2 illustrate the workflows of the conventional approach and the new KPMS approach respectively. By implementing KPMS, various manual operations of data collection in the conventional approach are automated by applying RFID and sensor. Moreover, decision-making processes of production planning and machine selection are supported by knowledge-based decision supports provided by KPMS. As shown in Table 5.1, the comparison of the conventional approach and the KPMS approach in managing various production activities is summarized.
Figure 5.1 Workflow of the Conventional Approach
Figure 5.2 Workflow of the KPMS Approach
Table 5.1 Comparison of Conventional Approach and KPMS Approach in Managing Production Activities

<table>
<thead>
<tr>
<th>Production activities</th>
<th>Conventional approach</th>
<th>KPMS approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production planning</td>
<td>Formulated by production supervisors based on their own experience</td>
<td>Formulated by CBR in KPMS’ knowledge-based engine</td>
</tr>
<tr>
<td>Collection of products’ transfers information</td>
<td>Products’ information is recorded manually by production staff</td>
<td>Products’ information is captured by RFID automatically in RFMC module</td>
</tr>
<tr>
<td>Collection of machine status data</td>
<td>Data of machine status is recorded manually by production staff</td>
<td>Data of machine status is captured by sensors automatically in RFMC module</td>
</tr>
<tr>
<td>Machine selection in dealing with machine breakdown problems</td>
<td>Decision of machine selection is made based on staff experience and judgment</td>
<td>Decision of machine selection is supported by machine flexibility assessment</td>
</tr>
<tr>
<td>Setting performance measures and weightings for measurement</td>
<td>Determined by management level through meetings</td>
<td>Determined by knowledge rules in K-PM module</td>
</tr>
<tr>
<td>Data analysis for performance measurement</td>
<td>Data is collected from various sources and transformed into performance index manually by staff</td>
<td>Data is retrieved from the data warehouse and transformed into performance index by K-PM module</td>
</tr>
</tbody>
</table>

The pre-requisites required to make the system work in other environments are provided as follows:

- Cases in the case repository can be retrieved by nearest neighbor retrieval method within a reasonable case retrieval time.
- Machine status such as operation and idle time can be recognized by a change of physical state, so that sensors can be used to collect the data of machine status.
The product value is high and it does not contain metal and liquid that will affect the readability of RFID.

The key performance indicators used by the company are quantitative, so that they can be calculated by knowledge rule inference.

5.3 Results of KPMS implementation in YeeFung Polyfoam Limited

To validate the proposed KPMS feasibility, the KPMS prototype’s development and implementation in a helmet manufacturer, YeeFung Polyfoam Limited, have been described in Chapter 4. To verify the system implementation’s results, a quantitative measurement of the KPMS’ effectiveness in providing knowledge-based decision support was conducted. The comparison of performance criteria before and after KPMS implementation is illustrated in Table 5.2. Meanwhile, the measurement areas of productivity, production cost, quality, asset utilization, and flexibility are adopted. It is noted that KPMS improves YeeFung Polyfoam Limited’s manufacturing operations in five different categories, namely, productivity enhancement, production cost reduction, quality improvement, asset utilization improvement, and flexibility enhancement.

(i) Productivity enhancement

The manufacturing processes’ productivity has been enhanced significantly as RFID and sensor technologies and knowledge-based engine are adopted in KPMS. These capture manufacturing data and provide decision support for production planning and machine selection, respectively. For example, the RFID readers and antennas installed in the production floor’ portals and machine cells will automatically read the data from the RFID-tagged WIP goods when transferred to different floors. This is because RFID tags are attached on every WIP product.
Table 5.2 The Measurement Areas of KPMS Implementation in YeeFung Polyfoam Limited

<table>
<thead>
<tr>
<th>Measure areas</th>
<th>Assessment factors</th>
<th>Before KPMS implementation</th>
<th>After KPMS implementation</th>
<th>% of improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity</td>
<td>Average Order fulfillment time 30 days 6136/day</td>
<td>22 days 7425/day</td>
<td>27%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Average throughput</td>
<td>21%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production Cost</td>
<td>Overtime cost $8220/day</td>
<td>$6300/day</td>
<td>23%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Labor cost $22500/day</td>
<td>$15000/day</td>
<td>33%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reproduction cost $130200/month</td>
<td>$52080/month</td>
<td>60%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Scrap cost $78120/month</td>
<td>$65100/month</td>
<td>17%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Handling cost $12672/month</td>
<td>$4224/month</td>
<td>67%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Delay of shipment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loss of missing goods $39060/month</td>
<td>$7812/month</td>
<td>80%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>First pass yield</td>
<td>92%</td>
<td>97%</td>
<td>5%</td>
</tr>
<tr>
<td>Quality</td>
<td>Defect rate 4%</td>
<td>2%</td>
<td>2%</td>
<td></td>
</tr>
<tr>
<td>Asset utilization</td>
<td>Machine availability 93%</td>
<td>96%</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Overall equipment effectiveness (OEE) 83%</td>
<td>88%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Flexibility</td>
<td>Planning time of dealing with machine problems 90 minutes</td>
<td>25 minutes</td>
<td>72%</td>
<td></td>
</tr>
</tbody>
</table>

The RFID’s automatic data collection capability assists in visualizing the production floors’ operations by providing the staff with accurate and updated data of WIP goods. With the adoption of RFID technology, the manual operation processes in the conventional approach, such as recording WIP goods’ information and checking their quantity, are eliminated. Further, the time spent by production staff on
finding the WIP goods during production processes is significantly reduced.

On the other hand, the KPMS’ knowledge-based engine employs the CBR technique to provide production supervisors with decision support in formulating production plans and crafting resource allocation decisions. As production is planned effectively by manipulating the knowledge-based decision support, the probability of committing mistakes within various production processes — such as transferring the WIP goods to a wrong production shop floor or producing the wrong quantity or model — is reduced. Further, the machine flexibility (MF) measure, which is determined through the operations data collected by sensors, assists production supervisors in selecting suitable machines for resuming production when uncertainties such as machine breakdowns occur. Since MF displays each machine’s production capabilities in handling a particular product type, production supervisors can assign the production order to another machine with similar capability, thereby reducing machine setup time and maintaining productivity. By implementing KPMS in YeeFung Polyfoam Limited, the average order fulfillment time is reduced by 27% while the shop floor’s average daily throughput is increased by 21%. The productivity of production process is enhanced significantly.

(ii) Production cost reduction

Since the WIP goods’ product information and location are tracked by RFID technology in real time, the production staff are relieved from non-value-added activities such as manually recording the WIP goods’ information and finding missing WIP goods. As a result, overtime and the number of data entry staff are cut down. Moreover, the WIP goods’ location is recorded in the system accurately by RFID, and loss is decreased significantly. Thus, overtime cost, labor cost, and product loss are trimmed down after system implementation.
As production planning is performed effectively by the KPMS’ decision support function, the costs of reproducing products that have been wrongly processed, as well as the scrap cost, are greatly reduced. The progress of production orders is likewise monitored effectively, thereby lessening the time and cost of handling late delivery. Further, the physical asset operations’ performance is monitored by capturing data in the RFMC module, and their utilization is optimized through production planning. This reduces machine failure as well as maintenance cost.

(iii) **Quality improvement**

By considering machine flexibility during selection, machines with similar capabilities can be assigned to produce the same product. As demonstrated in the past operations data, selecting the machine which could produce products effectively helps to maintain quality within acceptable control limits. Thus, the first pass yield is increased by 5% and the defect rate is decreased by 2%, reflecting an improved quality of production.

(iv) **Asset utilization improvement**

KPMS captures physical asset operations data by RFID and sensor technologies, providing production supervisors with knowledge-based decision support for planning the resource allocation for various production orders. In the recommended solutions for retrieved historical cases, the production flow, machines used, duration of production, and performance scores are involved. These recommended solutions can be tapped or revised by production supervisors to solve new production planning problems. Therefore, it aids production planners in selecting the right machines for fulfilling orders by leveraging past experience and performance scores. This improves the effectiveness of utilizing physical assets by assigning suitable products
to machines with particular capabilities. Thus, machines are maintained at a steady state, decreasing machine downtime and enhancing availability.

(v) **Flexibility enhancement**

After KPMS implementation, the time required by production supervisors to reallocate job assignments when encountering unpredictable machine problems is trimmed down significantly. The machine flexibility assessment function of the KPMS provides production supervisors with the supporting data to select suitable machines that will undertake the incomplete jobs. The production floor’s flexibility in dealing with unpredictable changes is improved.

### 5.4 Discussion of KPMS contribution

The proposed KPMS enhances the manufacturing companies’ performance by facilitating maximum utilization and effectiveness from production assets, which is the ultimate purpose of physical asset management. Performance measurement enables production managers to understand the effect of their resource allocation decisions through an overall performance index. Because it is dynamically capable of selecting appropriate performance indicators based on company objectives, it is suitable for the current competitive environment where companies occasionally need to revise their strategies and objectives. The importance of performance criteria will be adjusted by the system to react to changes in company objectives.

Moreover, the system encourages companies to continuously improve their physical asset utilization. After determining the overall performance score, the assessed resource allocation decision, as a new case, is evaluated against similar cases in the past; these cases are retrieved from the case repository to realize current performance and identify areas for improvement. Consequently, it suggests ways for
improving performance based on past experiences. The new case on resource allocation will be retained subsequently in the knowledge repository.

With the integration of RFID and sensor technologies, the proposed KPMS provides manufacturers with accurate performance assessment for enhancing productivity and improving product quality during production planning. From the practical view, this system helps manufacturers in selecting the appropriate machine for replacing a broken one.

Moreover, the machine flexibility assessment method proposed in this study considers three key performance dimensions: efficiency, quality, and reliability. Manufacturers are able to compare relative machine flexibility with others within a short period of time. Further, with the aid of RFID and sensor technologies, data collection accuracy is enhanced, particularly when measuring machine efficiency to perform a specific job order.

From an academic view, this research proffers three major contributions. First, a systematic process design is presented to establish a knowledge-based performance measurement system and support machine flexibility assessment and relevant performance measurement. Second, machine flexibility measurement methods found in studies on performance measurement mainly focus on efficiency while other performance indicators such as quality and machine breakdown rate are ignored. In KPMS, the machine flexibility measurement method evaluates relative change in machine performance regarding efficiency, quality, and reliability when shifting from one job to another. In other words, the method helps to assess relative flexibility, as well as identify potential problems that may arise during the job shift. Third, this research demonstrates a methodology for transforming machine status and product identity into information status using sensor and RFID technologies.

With the help of these data collection technologies, the system performs product
and machine status tracking which eliminates the traditional manual data collection problem. Hence, the data inaccuracy problem affecting performance measurement quality in the conventional approach is solved.
Chapter 6 Conclusion

This chapter presents a research summary and highlights the study’s industrial contributions. The limitations of the research are explained and suggestions for future work are described.

6.1 Summary of Research Work

In recent years, the ability to provide efficient and cost-effective response to unpredictable changes has been regarded as a critical success factor for manufacturing companies to survive in today’s dynamic and customer-oriented environment. Manufacturing companies must maintain higher flexibility and responsiveness in their production systems through better utilization of physical assets.

This research study recognizes that physical asset management (PAM) initiatives are worthwhile, helping companies achieve lifetime effectiveness, maximum utilization, and returns from physical assets. This philosophy enables manufacturing companies to cope with a dynamic and responsive operations environment by fully utilizing limited physical assets’ production capabilities and maintaining a steady productivity level without asset breakdown.

From the review study on PAM, the majority of research focuses on the adoption of maintenance strategies, systems, and fault diagnosis tools in managing maintenance activities. However, few research studies are proven to enhance lifetime effectiveness and physical assets utilization through proper production planning, performance measurement, and monitoring of asset operations. This research aims to propose a knowledge-based performance measurement system (KPMS) for manufacturing companies to support the decision-making tasks of production planning and machine selection on the dynamic production floor. KPMS integrates
emerging automatic data collection technologies of RFID and sensor with the performance measurement concept to measure the physical asset operations and evaluate the effectiveness of resource allocation.

Further, the KPMS involves a knowledge-based engine that provides decision support functions regarding production planning and machine flexibility measurement for machine selection. The KPMS system architecture and principle, which consist of two modules, RFMC and K-PM, have been constructed, as described in Chapter 3. A KPMS prototype has been developed and successfully implemented in Yee Fung, a helmet manufacturing company, and its operations mechanism has been demonstrated in Chapter 4. In summary, case study results proved that the proposed system improves the production floor’s operational efficiency and physical asset utilization by providing the right knowledge in supporting decisions of production planning and machine selection.

6.2 Contributions of the Research

KPMS’ key contributions to manufacturing companies are summarized as follows:

(i) The unique feature of KPMS is that it helps manufacturing companies achieve the physical asset management initiative in optimizing lifetime effectiveness and providing better production planning and monitoring of asset operations. It fills the gap in current PAM research, which solely focuses on maintenance studies and provides a new research direction on system development using state-of-the-art technologies.

(ii) The KPMS can capture real-time operational data of physical assets from production shop floors. As it captures the manufacturing data automatically by merging RFID and sensor technologies, the physical asset operations data
including physical location of WIP goods and machine status are collected accurately and efficiently without manpower consumption for data collection.

(iii) The physical assets status, including WIP goods and machines, is captured in the system. Therefore, the system significantly increases the production floor’s transparency. Thus, it helps manufacturing companies reduce the use of resources in locating missing WIP goods and tracking the production progress, which eventually decreases production costs.

(iv) In KPMS, a knowledge-based engine is developed for production managers to formulate production plan efficiently to cope with different customer orders under a dynamic production environment. The CBR technique is employed to retrieve past cases of production planning for solving new problems. The CBR engine reduces reliance on experienced staff to make decisions and prevents the loss of knowledge when employees leave.

(v) The system provides performance measurement function and utilizes the RBR technique for transforming the manufacturing data, which is integrated from distributed sources into performance indexes for evaluating the manufacturing performance. The performance indexes likewise help validate the effectiveness of decisions made in production planning and resource allocation.

(vi) A machine flexibility assessment method is designed for supporting the decision-making task on machine selection. It enables production supervisors to consider each machine’s capabilities when producing a specific product. By acquiring this information, the production supervisor can react quickly to uncertainties on the shop floor, such as machine breakdown problems.

6.3 Research Limitations

The limitations of the research are addressed as follows:
(i) The KPMS proposed in this research adopts RFID technology to capture the operations data of physical assets, including WIP goods for supporting performance measurement and machine flexibility assessment functions. However, if coverage of data tracking extends to all products in the whole manufacturing process, a large number of RFID devices, including readers and antennas, are required to be installed in numerous shop floors. A great amount of RFID tags are needed for all products. This leads to the problem of high implementation cost. Thus, small- and medium-sized manufacturing companies may not be able to afford the implementation of the system. In addition, it is not cost effective to implement RFID technology in the item-level for tracking low cost products.

(ii) The KPMS’ knowledge-based engine utilizes CBR technique to retrieve similar past cases and manipulate knowledge for decision support in formulating a production plan. To retrieve cases with high similarity value to solve new production planning problem, it is necessary to store enough historical cases of production plans in the repository. This requires manufacturing companies to input past cases, including problems and production planning solutions into the case repository at the beginning of system implementation, which is a very time-consuming task.

(iii) During the case retrieval process, the nearest neighbor method was utilized to retrieve similar cases from the repository. Since the similarity value between the input case and each case stored in the repository will be calculated and compared using the nearest neighbor method, case retrieval time will become longer if the repository is large. Thus, the current CBR system cannot cope with a large scale case retrieval problem such as over 10,000 cases in repository.

(iv) The proposed system helps to achieve the physical asset management initiative
that only focuses on physical assets performance measurement. It does not measure and take into account other intangible assets such as intellectual capital, copyright, and patents.

(v) The proposed system is incapable to deal with intangible performance measurement.

### 6.4 Suggestions for Future Work

The following suggestions for future work of KPMS are provided to improve the system’s adaptability.

(i) The proposed system is implemented in a helmet manufacturing company, as described in Chapter 4. It is suggested that the system can be implemented in other manufacturing companies of different industries, such as toy, garment, and electronics, to further validate the system.

(ii) Another case retrieval method such as the case-cluster approach may be utilized in the system to replace the nearest neighbor method to reduce case retrieval time when a sizeable amount of cases has accumulated in the repository. The case-cluster approach will compare the similarity between the input case and each case cluster in the repository. It will then select the case cluster with the highest similarity and compare the input case with each case in the cluster. Compared with the current nearest neighbor method, which determines the similarity of input case with all cases in the repository, the case retrieval time is considerably faster.

(iii) The proposed system assists manufacturing companies in making the right decisions in production planning and machine selection to enhance the effectiveness and utilization of physical assets. The research scope can be extended to include other production resources such as workers and operators.
The consideration of job assignment to production workers is recommended for addition to the decision-making process to effectively utilize each worker’s capabilities.

(iv) The performance of the proposed system should also be monitored by incorporating self-recovery ability in order to enhance the robustness of the proposed system to internal and external changes and uncertainties, so that self-improvement of the system can be achieved.

In summary, a KPMS design that integrates RFID and sensor technologies, performance measures, and AI techniques for measuring the performance of physical asset operations and supporting production planning decisions is a novel concept. The proposed system’s ultimate goal is to enhance the effectiveness of physical asset utilization during its operation lifetime, which is seldom addressed in related literature. It is hoped that this research may increase the awareness of manufacturing companies in applying physical asset management initiatives to improve manufacturing operations.


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