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Complexity Analysis in Maintenance Systems

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COMPLEXITY ANALYSIS IN MAINTENANCE SYSTEMS

By

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Abstract

COMPLEXITY ANALYSIS IN MAINTENANCE SYSTEMS

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Master of Applied Science

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Complexity is a very broad subject that applies to project management, engineering design and manufacturing, arithmetic, software, statistics, etc. In maintenance systems, complexity can be defined based on technical and managerial aspects of a maintenance project. Because relative complexity between two projects can be used as a yardstick for resource allocation between them, quantifying the complexity becomes important. To quantify the complexity of maintenance projects, this thesis reports two models.

In uncertain situations, a fuzzy graph-based model is developed that determines relative complexities of maintenance projects based on experts' opinions with respect to technical and managerial aspects. These aspects may not be measured precisely due to uncertain situations. The model uses an aggregation operator to mitigate conflict of experts' opinions on complexity relations. Using a fuzzy relation matrix representing the degrees of membership of relative complexities, the model maps the fuzzy graph into a scaled Cartesian diagram.

Also, complexity of a maintenance project can be investigated through time to repair (TTR). Performing statistical analysis shows that human cognition and project complexity have significant influence on TTR. These influential factors can be studied by a learning curve. Due to the nature of maintenance calls for repairs, a learning curve model made up of two segments is proposed. A project complexity can be derived from the learning curve at the breakpoint time. Taking into account human cognitive abilities, the breakpoint indicates the required number of trials in order to reach mastery level for performing certain tasks unsupervised.

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Nomenclatures

n	total number of nodes/projects
i	project index, i=1,2,…,n
j	project index, j=1,2,…,n
V	a crisp set of nodes representing projects
$\tilde{R}$	a fuzzy set of complexity relations between projects
$\mu_{\tilde{R}}(P_i, P_j)$	degree of membership for relative complexity for $P_i \rightarrow P_j$
$\tilde{G}(V, \tilde{R})$	complexity graph composed of a crisp set of nodes (V), a fuzzy set of complexity relations ($\tilde{R}$)
C_{P_i}	complexity of project i=1,2,…,n
$\tilde{M}$	fuzzy complexity graph matrix with element m_{ij} $\forall i, j$
$\tilde{M}'$	expected value of matrix $\tilde{M}$
m_{ij}	element of matrix M
$\tilde{r}$	the first projection of M'
$\tilde{c}$	the second projection of M'
$\mu_{(\tilde{r})}$	degree of membership for relative complexity of a project
$\mu_{(\tilde{c})}$	degree of membership for relative relaxation of a project
Δ	coefficient factor

β	Human cognitive value in learning curve
α	Scale parameter in learning curve
t_0	a task's breakpoint time
$\left\| \mu_{P_i \to P_j} \right\|$	relative cardinality
t	time
λ	Common failure rate in Poisson distribution

Abbreviations

AHP	Analytic Hierarchy Process
ANOVA	Analysis of Variance
CDSM	Complexity Design Structure Matrix
DSM	Design Structure Matrix
EMIS	Enterprise Maintenance Information Systems
FD	Functional Domaine
MF	Module Finding
RTS	Restricted Topological Sorting
SSE	Sum of Square Error
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TTR	Time to Repair
WLC	Wrights Learning Curve

Chapter1

Introduction and literature review

1.1 Background

While complexity in maintenance is an extremely important subject to most organizations, it is neither well understood nor adequately characterized in the literature. To discuss complexity, it is first necessary to precisely define it. However, there is no unique definition for complexity that can be used for all the fields of study, such as biology, information theory, computer science, and manufacturing systems. According to the Merriam-Webster dictionary, "complex" is defined as "composed of two or more parts; hard to separate, analyze, or solve". Alternatively, Oxford dictionary defines the word "complex" as "consisting of many different and connected parts; not easy to understand; complicated". The common element in both definitions is that a complex system is composed of numerous but related parts, and that it is difficult to understand. Therefore, the words complex and complexity should be defined according to the field of study.

Generally, complexity is a very broad subject. It has been studied in many fields, such as project management, engineering design and manufacturing, arithmetic, chaos theory, entropy, fuzzy logic, games, information, philosophy, software, and statistics. As a result, several models have been developed to quantify complexity (Bashir & Thomson, 1999; Bashir & Thomson, 2001; El-haik & Yang, 1999; Rodriguez-Toro et al., 2003; Smith & Jenks, 2006). Complexity can be used as a yardstick for budgeting, resource allocation, and planning in enterprise maintenance projects. Complexity of a maintenance project can be determined based on technical and managerial aspects of the project that cannot be precisely measured due to uncertainties. In a wide variety of systems, automation is a significant substation of mechanical, electrical or computerized actions representing human effort. However, automation has a limited application in maintenance systems because of the impact of human intelligence in diagnoses and repairs. Moreover, as organizations move towards shorter production times, workers must regularly learn new skills, technology, and processes. Therefore, workers must cross-train and be competent at multiple tasks simultaneously. As a result, a substantial portion of the workforce will constantly be on the steep portion of their learning curve regarding their ability to perform any particular task.

Human behaviour is highly flexible because man switches from one task to another, either in response to the availability of new information or as a function of fluctuations in the temporary goals that guide human actions. Figure 1.1 shows a general learning process for a repetitive task. It shows that a worker learns to perform tasks more efficiently with instruction and repetition. In other words, a learning curve or experience curve is a graphical representation of the changing rate of learning (in the average person) for a given activity.

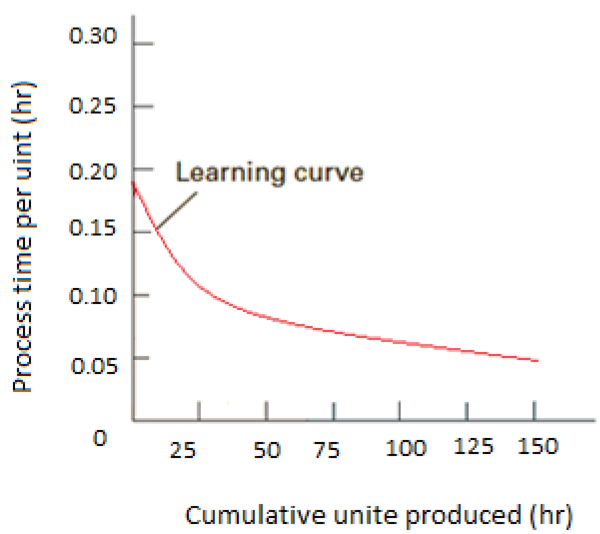


Figure 1.1. General learning curve for a repetitive task (Pegels, 1969)

Reductions in operation times achieved through the effects of learning curves can directly translate to cost savings for manufacturers. Learning curves, also known as progress functions, cost-quantity relationships, cost curves, product acceleration curves, improvement curves, performance curves, experience curves, or efficiency curves, are essential for functions such as setting production goals, cost control, and resource allocation.

Learning curves have been receiving increasing attention by researchers and practitioners for almost seven decades, and there have been several models that researchers have utilized. Some of these models are the log-linear model (Wright, 1936), The Stanford-B model(Asher, 1956) , DeJong's learning (DeJong, 1957), Pegel's exponential function (Pegels, 1969), Knecht's upturn model(Knecht, 1974) , Levy's adaptation function (Levy, 1965) and Yelle's product model(Yelle, 1976) power low model (Rosenbloom & Newell, 1987) . The rate and shape of improvement are fairly common across tasks. Among several models that researchers have investigated, the power function fit appears to be the most robust, regardless of the methods used. Heathcote et al., (2000) suggest that the power law might be an artefact arising from averaging (Anderson & Tweney, 1997). Further, the exponential function may be the best fit when individual subjects employ a single strategy. Differentiation between the power and exponential functions is not just an esoteric exercise in equation fitting. If the learning process follows an exponential, then learning is based on a fixed percentage of what remains to be learnt. On the other hand, if the learning process follows a power law, then learning slows down as it continues.

Recently, there has been an increasing amount of attention among researchers in industrial engineering attempting to account for the opposite phenomenon: that there is a breakpoint in the learning study. The breakpoint, or steady state, of the learning curve occurs when a person knows a task well enough to perform it unsupervised and without spending more time to learn the task (Figure 1.2). After this point, individuals perform certain tasks in a standard time. Two influential factors on the breakpoint are human cognitive abilities and task complexity.

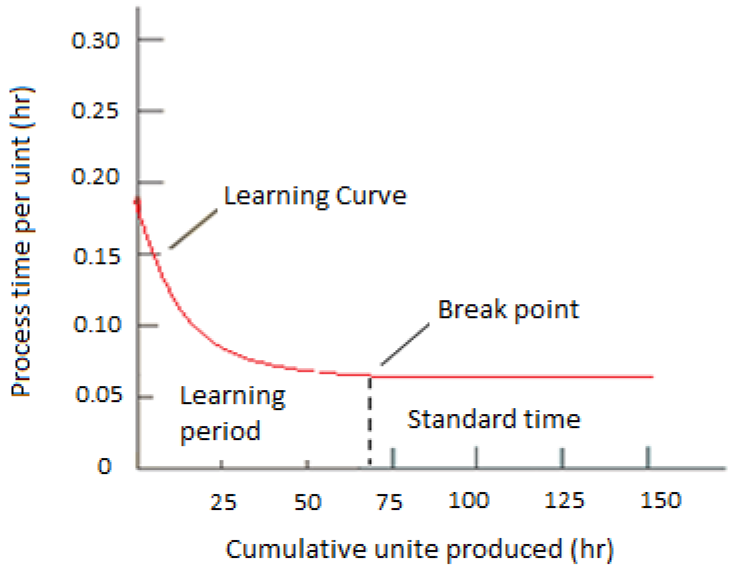


Figure 1.2. Learning curve with breakpoint

Human cognition is a significant factor in the learning process, and is the most consistent factor in all systems where humans are a part of the systems. Wang (2005) explored the cognitive foundations of human traits and cognitive properties of human factors in engineering and societies. Motivation and cognitive abilities represent two basic determinants of learning and work performance. Numerous studies have investigated the role of cognitive - intellectual abilities in predicting individual differences in job performance. The most common conceptualization of ability motivation interaction in industries and organization psychology is that suggested by Vroom (1964), who indicates that when motivation is low, both low and high ability individuals demonstrate similar low levels of performance. However, when motivations are high, performance variability due to individual differences in ability will be more obvious. Bransford et al., (1986) investigates areas in which technology can facilitate learning in schools. When human cognitive abilities are taken into account within the learning process, the complexity of the assigned task becomes a nuisance factor.

Cognitive abilities are the brain-based skills and mental processes that are needed to carry out any task – from the simplest to the most complex. Every task can be broken down into the different cognitive skills that are needed to complete that task successfully. If they are not used regularly, a person's cognitive abilities will diminish over time. Fortunately, these skills can also be improved at any age with regular practice.

In light of this, a great deal of work has been performed by many researchers. It has been revealed that a large portion of human performance related problems was attributed to the complexity of tasks because a complicated task places a substantial cognitive demand on task doers (Campbell & Gingrich, 1986). It is expected that human performance would be impaired due to a huge amount of cognitive demands, which exceeds the ability of human operators (Stassen et al., 1990). Fortunately, these skills can also be improved at any age with regular practice (Latham, 2006). These cognitive abilities include:

Alternating Attention: The ability to shift the focus of attention quickly.

Auditory Processing Speed: The time it takes to perceive relevant auditory stimuli, encode, and interpret it and then make an appropriate response.

Central Processing Speed: The time it takes to encode, categorize, and understand the meaning of any sensory stimuli.

Conceptual Reasoning: Includes concept formation, abstraction, deductive logic, and/or inductive logic.

Divided Attention: The capability to recognize and respond to multiple stimuli at the same time.

Fine Motor Control: The ability to accurately control fine motor movements.

Focused (or Selective) Attention: The ability to screen out distracting stimuli.

Visual spatial Classification: The ability to discriminate between visual objects based on a concept or rule.

Visual spatial sequencing: The ability to discern the sequential order of visual objects based on a concept or rule).

Visual Perception: The ability to perceive fixed visual objects.

Visual Processing Speed: The time it takes to perceive visual stimuli.

Visual Scanning: The ability to find a random visual cue and the ability to follow a continuous visual cue.

Working Memory: The ability to hold task-relevant information while processing it.

Through these abilities, complexity of a task can be derived from the learning curve. A complex task requires more human cognitive abilities. Consequently, the worker needs more time to reach standard time for performing the task. Due to the following reasons, a new learning curve for maintenance task is required that is made of cognition factor and breakpoint time.

1- A maintenance task is a repetitive in a random and long interval time
2- A maintenance task requires more time to be performed because of diagnosis process
3- A maintenance task requires deeply human cognitive abilities

Therefore, existing learning curve models may not be suitable for maintenance task. Also, there is a little attention has been paid to quantify the complexity of a maintenance task.

1.2 Literature Analysis

A comprehensive review of the published literature during the period 1967-2010 is presented below. Figure 1.3 presents a stacked bar chart of publications on complexity based on the techniques and application used in the publications. Also, Figure 1.4 shows a stacked bar chart of publications with respect to the method and type of input data. Sources of reviewed journals and conference papers are:

- *Architectural Engineering and Design Management*
- *Concurrent Engineering: Research and Applications*
- *Engineering Technology Management*
- *Harvard Business Review*
- *Learning Curves in Manufacturing. Science*
- *Environment and Planning B: Planning and Design*
- *International Journal of Reliability, Quality and Safety Engineering*

- *International Journal of Production Research*
- *IIE Transactions*
- *Research Policy*
- *Project Management Journal*
- *Industrial Engineering*
- *Peabody Journal of Education*
- *Memory & Cognition*
- *IEEE Transactions on Engineering Management*
- *International Journal of Production Research*
- *Engineering Design*
- *The Accounting Review*
- *Intelligent Manufacturing- Special Issue on Advanced Technologies for Collaborative Manufacturing*
- *Environment and Planning B: Planning and Design*
- *Management Science*
- *Journal of Production Economics*

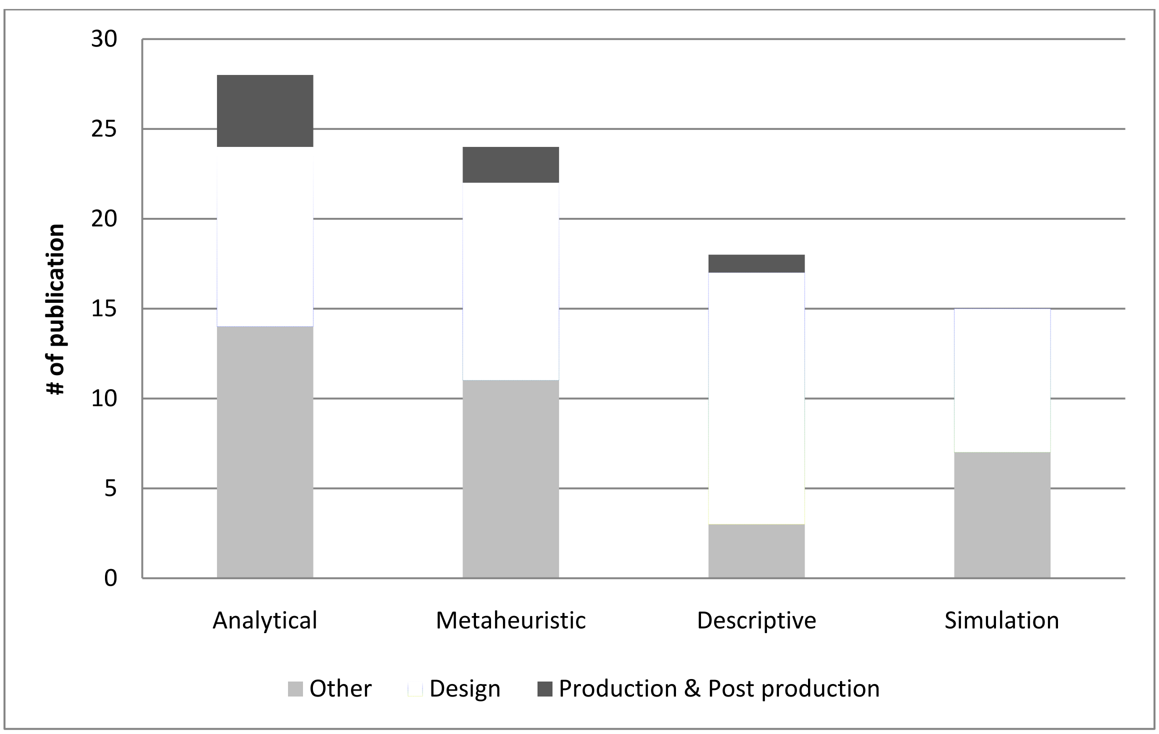


Figure 1.3. Classification of techniques and applications

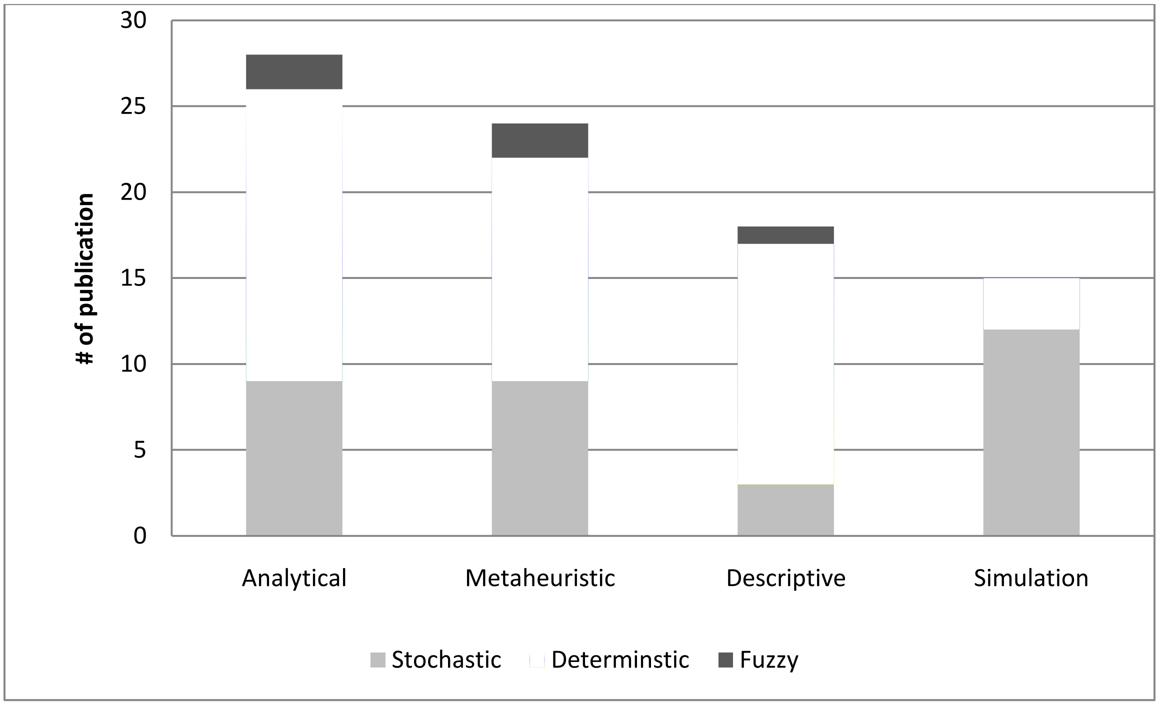


Figure 1.4 Classification of methods and type of input data

1.3 Literature Review

Today's competitive environment means that the manufacturing systems need to respond rapidly to changing market demands, with the focus on higher quality products at a lower price. Therefore, industrial entities face increasing challenges in their manufacturing and assembly systems where different results and a greater variety and diversity in products are demanded. On the other hand, products become more complex in terms of their production. Nowadays, customers' needs have expanded and their many miscellaneous requirements are complicated in order to bring the functions to their products that they seek. In addition to variety, products should be offered with high quality in conjunction with a low price. All these factors impose complexity to all stages of development, such as design, manufacturing, and maintenance.

A number of experts and researchers distinguish complex processes in quite a number of specific ways. For example, Burns & Stalker (1961) considered managing a process, which comprises of unfamiliar activities in unfamiliar environment as "complex". Also, Perow (1965) defines the complexity of a task as the degree of difficulty of the search process in performing the task, the amount of thinking time required to solve work-related problems, and the body of knowledge that may provide guide lines for performing the task.

Further, Sors et al., (1981) presented a rating system for measuring mould maintenance complexity that utilized the outer and inner surface complexity. Steward (1981) presented Design Structure Matrix (DSM) method to model project tasks. The precedence relationship is presented by a value in the lower diagonal section of the matrix. Also, an iteration relationship is shown by the upper diagonal section. These values are probabilities of one task going to another task in sequence. Using the expected value of this matrix is an efficient ordering of the tasks. The expected value of the matrix can be calculated by repeatedly multiplying the probability matrix to itself until the steady-state is reached.

McFarlan (1981) suggested that uncertainty required adapting one's management style to the project's uncertainty profile as measured by the dimensions of project size, project structure, and experience with the technology.

In respect to the engineering design of a product, the independence and the information axioms as foundations for a design were proposed by Suh (1984). The independence axiom requires that all functional requirements be independent. The information axiom requires the information content in the design be minimized, where the information requirement is the complexity measures. These axioms and the complexity measures can be defined by an array that its elements are functional requirements, design parameters, and process variables. Further, the complexity can be classified as organized or disorganized variables (Weaver, 1984). Weaver assumed the organized complexity is characterized by a small number of significant variables that are tied together in deterministic relationships. On the other hand, the disorganized complexity is characterised by a huge number of variables that are tied together by stochastic relationships.

Gibson & Senn (1989) studied system structure and software maintenance. Their study was designed to allow for the preliminary investigation of the relationship between system structure (complexity) and maintainability. This study was conducted to examine how complexity differences exhibit themselves in a system.

Also, complexity can be defined in the physical and functional domains. In the physical domain, complexity is defined as the inherent characteristic of physical components, like algorithms, products, processes, and manufacturing systems. As a result, it is inferred that the more parts a physical object has, the more complex it is. On the other hand, the complexity is defined as a measure of uncertainty in achieving a set of tasks defined by FD (Suh, 1990).

Complexity in maintenance projects is generally considered in relation to technical, managerial and human learning aspects. Ambiguity and project complexity lead to information inadequacy. Ambiguity refers to a lack of awareness of the maintenance crew about a system (i.e., subsystem interrelation, geometry, topology, manufacturability, and assembly factors) (Riggs & Simth, 1993). A subjective approach to calculate the complexity of a product based on the physical size of its components was proposed by Ulrich et al., (1993). Project complexity means that the crew deals with a system made up of many subsystems with different functions and states, so that the effect of functions is difficult to assess (e.g., Kauffman, 1993).

Boothroyd et al., (1994) reported a novel tooling cost estimation model based on a part geometric complexity. The model takes into account the number of hours required for maintenance and shop hourly rate.

Calinescu et al., (1998) presented a comparative analysis among quantitative approaches for complexity measures. This study concluded that entropic measures offered substantial advantages. Dvir et al., (1998) proposed an empirical classification method that used degrees of technical uncertainty and complexity of the project.

According to Xu (2000), system components can operate as independent elements. However, when they are incorporated into a system, their behaviour depends on interactions with other system components (Siggelkow, 2002). In relationship to the engineering design of a product, Denker et al., (2001) described the rows of the design structure matrix as the inputs and the columns as the outputs to complete a task and that the scope of a process should be narrowed by limiting the iterations.

The project complexity also can be analyzed through two major aspects: technical and managerial. However, technical and managerial aspects of a project are major pieces of information that cannot be measured precisely because of uncertain situations (Pich et al., 2002). As a result, project failures are numerous in practice; for example, budget and schedule overruns compromised performance, and missed opportunities (Tatikonda & Rosenthal, 2000).

Using three dimensional CAD drawings and analyzing the assembly of a product, manufacturability complexity has been quantified (Rodriguez et al., 2003). Although this is the more concrete side of looking at complexity, there is also a more abstract side, which deals with information and decisions.

In conjunction with design complexity, Thomas & Singh (2006) explained how to reduce complexity in a design project by using Six Sigma and taking into account customer opinion. Their model differentiates between value-added and non-value added complexity. Sinha et al., (2006) developed a model for resource allocation among projects based on complexity measures.

Seol et al., (2007) used the restricted topological sorting (RTS) and the module finding (MF) algorithms as decomposition methods to reduce the complexity of a project. The results of this approach can be used for the allocation of tasks among a group of designers. Alternatively, they proposed a network approach to define a modularity index in complex products.

Sosa et al. (2008) studied the complexity measures in the software products by using DSM. In another related study, Gero & Sosa (2008) used entropy functions in their computational approach for complexity measures as a basis for mass customization in designs. Frizelle & Suhov (2008) gave a review of three case studies of the complexity of production systems in maintenance and commercial industry and developed mathematical methods stemming from these studies. Song & Kusiak (2009) studied the role of maintenance complexity and product diversity in customer oriented maintenance systems.

The geometry is defined as polygon meshes including coordinate values of vertices of the meshes making up the model. The topology is concerned with redundant references to vertices and edges that are shared by entities. The manufacturability deals with equipment setup time, manufacturing yield, direct supervision, and finishing. Also, the assembly factor takes into account the number of parts, assembly time, and assembly tools that are impacted by complexity (Rodriguez et al., 2003, Jenab & Liu, 2009). Also, a graph-based model to analyze the manufacturing complexity in non-fuzzy (crisp) situation is proposed by Jenab & Liu (2009). Their model uses cost utility function to construct the complexity graph and find the direction of the links. They use another measure called similarity in order to map the complexity graph in a Cartesian diagram. This model is not applicable to analyze the complexity of the maintenance projects in uncertain situations.

1.4 Shortcomings

1) In a maintenance project, there is no model to quantify complexity of tasks in fuzzy situations by taking into account technical and managerial aspects.

2) Due to the nature of maintenance projects, which are not repetitive tasks and are subject to a chance failure, there is a need to quantify the complexity by considering human cognition and learning curve.

3) There is no study on the amount of training required for maintenance projects to be performed without supervision.

1.5 Objectives

The major objectives of this thesis are:

Chapter 2 investigates complexity using a fuzzy model for enterprise maintenance projects.

> In this chapter, a fuzzy graph-based model to measure the relative complexity of projects is presented that uses an aggregation operator to mitigate experts' opinions over a complexity relation. Using a fuzzy relation matrix representing the degree of complexity, the model maps the fuzzy graph into a scaled Cartesian diagram that depicts the relative degree of complexity among projects.

Chapter 3 analyzes human cognitive abilities and complexity in maintenance.

> The learning curve for a repetitive job or task represents the relationship between experience and productivity. However, this is not applicable in maintenance because of chance failure. Therefore, a maintenance crew can do the task once in a while. With an instructor, the maintenance crew can learn the task and do it in a way that reduces the time and cost. In this chapter, a learning curve model for maintenance systems is reported that can be used to determine complexity of a task based on the breakpoint and human cognition factor.

Finally chapter 4 provides conclusions and future research.

Chapter 2

Complexity model for enterprise maintenance projects with fuzzy situation

2.1 Background

The term *enterprise* refers to a comprehensive framework used to manage and align an organization's processes, information technology, hard and soft resources, and projects. Today's enterprise performance depends on the safe, reliable and productive operations of assets. Therefore, having effective Enterprise Maintenance Information Systems (EMIS) becomes very important. The related literature on enterprise maintenance systems considers EMIS composed of Operational Reliability, Maintenance Economics, Human Factors, Maintenance Programs, and Maintenance Optimization Sub-Systems (Jenab & Zolfaghari, 2008). By collecting information from all enterprise divisions that are physically distributed across the environment, these sub-systems aim at managing maintenance projects. However, technical and managerial aspects of a maintenance project are major pieces of information that may not be measured precisely due to the uncertainty of many situations (Pich et al., 2002). As a result, project failures are numerous in practice, for example: budget and schedule overruns, compromised performance, and missed opportunities (Tatikonda & Rosenthal 2000). Therefore, adapting management style to the project uncertainty profile, as measured by the dimensions of the project size, project structure, and experience, is required (McFarlan, 1981). Also, a project empirical classification method was proposed that used degrees of technical uncertainty and the complexity of the project to map the overall uncertainty (Dvir et al., 1998). As complexity measures has become an efficient yardstick to manage a group of maintenance projects, having a quantitative model to analyze the relative complexity under uncertain situations is a must. There are several methods to analyze complexity. The knowledge base rule uses the knowledge encoded in some form such as rule-based systems, and decision tree. Generally, the construction of a complexity model has been carried out by interviewing experts in complexity aspects and painstakingly translating the experts' opinions into an appropriately structured set of rules (e.g., *if-then*) (Filev, 1997). Due to time consuming, complexity of consistency check, and difficulty of maintenance, knowledge base approach is not considered. Alternatively, fuzzy TOPSIS approach for complexity analysis is studied. Since the complexity criterion with the highest score has disproportionate impact in the complexity ranking process, the sensitivity analysis cannot be done with TOPSIS (Braglia et al., 2003). Also, Analytic Hierarchy Process (AHP) technique is considered to determine the preferential weight of relative complexity between projects. This approach works based upon three principles: 1) decomposition, 2) comparative judgements, and 3) synthesis of priorities. AHP has several shortcomings for complexity analysis, such as man-made inconsistency in pair wise comparisons, and rank reversal when new projects are introduced. Considering the simplicity of and efficiency of the proposed method, this chapter makes two contributions. First, by defining a fuzzy relation, a quantitative method for expressing the relative complexity among projects is presented. The method uses an aggregation operator to mitigate experts' opinions on a complexity relation. Second, a pictorial model mapped in a scaled Cartesian diagram to show relative complexity among maintenance projects is proposed. Outcomes of this graph can help in budgeting, planning and allocating soft and hard resources among projects. A hypothetical example for five maintenance projects is demonstrated to present the application of the model.

2.2 Method of Fuzzy Complexity Analysis

The impact of complexity on outcomes, which are realizable from maintenance projects over their life cycle has become a major concern in today's enterprise performance. Complexity measures can be derived from technical and managerial aspects of maintenance projects. However, quantifying these aspects is often uncertain and vague. As a result, most of the traditional tools for modeling, reasoning and computing, which are crisp, deterministic, and precise in character, may not be suitable for complexity analysis in maintenance. In this chapter, a fuzzy relation, which is an element of a fuzzy graph, is proposed to define complexity relations among projects. A fuzzy complexity graph composed of a set of fuzzy relations can be represented by a fuzzy matrix containing a list of all projects and the degree of membership of the fuzzy relative complexity. In crisp situation, the relative complexity means in what degree project *i* is more complex than project *j* denoted by $P_i \to P_j$. In uncertain situations, experts may express the fuzzy relative complexity between project *i* and project *j* by values in a range [0-10] where the spectrum of the linguistic variables and corresponding values in responding to the question of if P_i is more complex than P_j are 0=No(N) (i.e. Less or Equal), 1=Very Low(VL), 2=Low Plus(L+), 3=Low(L), 4=Low-Medium(LM), 5=Medium(M), 6=Medium Plus(M+), 7=Medium-High(MH), 8=High(H), 9=High Plus (H+), and 10=Very High(VH). Accordingly, the expert may express the complexity relation for $P_j \to P_i$ by any value in range [0-10]. By using a membership function, the degree of membership can be calculated for the fuzzy relative complexity obtained from experts. Since experts do not often agree on the relative complexity between projects, an aggregation operator is used to mitigate conflict of experts' opinions. As a result, the fuzzy matrix is composed of the aggregated degrees of membership. By using the first and the second projects of the expected value of the fuzzy matrix, the fuzzy complexity graph can be mapped into a scaled Cartesian diagram. This diagram and the membership function are the elements for computing the coefficient factor used for budgeting and resource allocation among projects in a maintenance system.

2.2.1 Fuzzy Complexity Relations

Consider the fuzzy relation $\tilde{R}$ that represents the relative complexity between the projects (Eq.2.1). The crisp relative complexity $P_i \to P_j$ determines if project *i* is more complex than project *j* by degree of membership (e.g., No=0 and Yes=1 in a non-fuzzy situation). In a fuzzy situation, the degrees of relative complexity can be defined by membership grades in a range [0-1]. Thus, the fuzzy relations are fuzzy subsets of $P_i \times P_j$, that is mapping from $P_i \to P_j$. Let $P_i, P_j \subseteq \tilde{R}$ be universal project sets, then $\tilde{R}$ is called a fuzzy relation on $P \times P$ (Figure 2. 1)

$$\tilde{R} = \left\{ (P_i \to P_j, \mu_{\tilde{R}}(P_i, P_j)) \,\middle|\, P_i \xrightarrow[i \neq j]{} P_j \subseteq P \times P \right\} \tag{2.1}$$

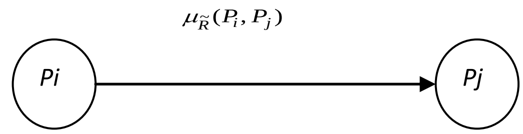


Figure 2.1. Degree of complexity relation between P_i and P_j

To calculate the degree of membership of the relative complexity defined in Eq.2.1, experts are required to express their opinions about in what degree project *i* is more complex than project *j* by a value in a range [0-10] where values around 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 denote No(N) (i.e., Less or Equal), Very Low(VL), Low Plus(L+), Low(L), Low-Medium(LM), Medium(M), Medium Plus(M+), Medium-High(MH), High(H), High Plus (H+), and Very High(VH), respectively. There are many functions for assigning the degree of membership to a fuzzy number (i.e., relative complexity). These functions must be convex and assign the degree of membership in a range [0-1] (Zimmermann, 2001). In this chapter, the membership function (Eq.2.2) is used for simplicity (Figure 2.2).

$$\mu_{\tilde{R}}(P_i, P_j) = \frac{1}{10}(\text{Relative complexity}) \tag{2.2}$$

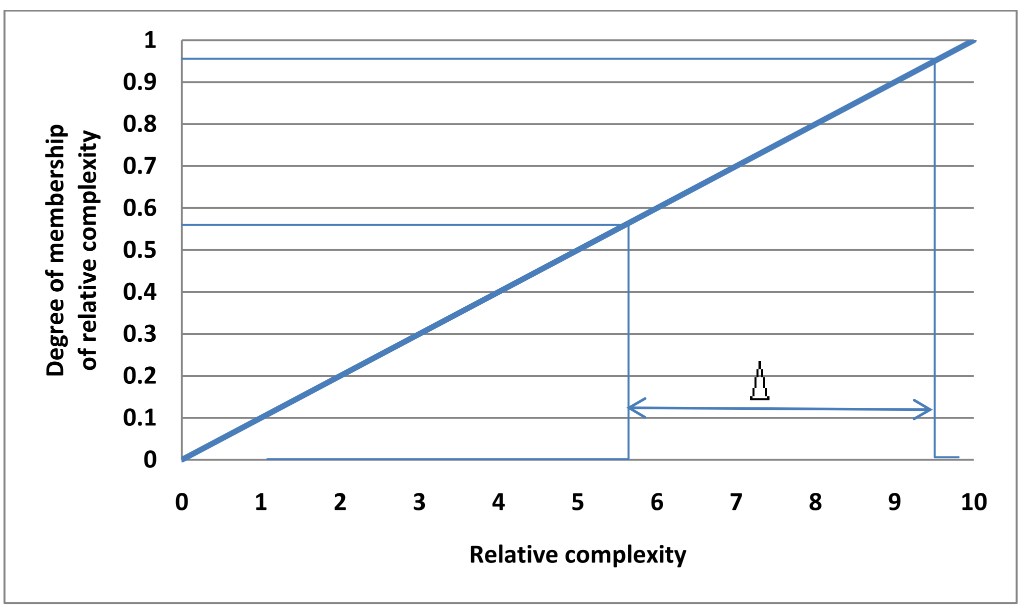


Figure 2.2. Membership function of complexity relation $P_i \to P_j$

Maintenance projects are often complex with slight differences in their technical and managerial aspects. Therefore, the experts' opinions differ substantially because they do not often agree on the relative complexity of various aspects of the projects. To dilute conflict in experts' opinions, a conflict resolution technique is required that uses aggregation operators in fuzzy situation. Aggregation operators are operations that combine two or more fuzzy expert's opinion sets. Here, a relative cardinality is used (Eq. 2.3).

$$\left\| \mu_{P_i \to P_j} \right\| = \frac{\sum_{all\,experts} \mu_{P_i \to P_j}}{total\ number\ of\ experts} \tag{2.3}$$

2.2.2 *Fuzzy Graph Complexity Model*

A graph is made of up a crisp set of nodes and a set of edges. Sometimes a pair of nodes is connected by multiple edges yielding a multi-graph. When a node is connected to itself by an edge, it is called a loop, yielding a pseudo-graph as shown in Figure 2.3. Finally, edges can also be given a direction yielding a directed graph (or digraph).

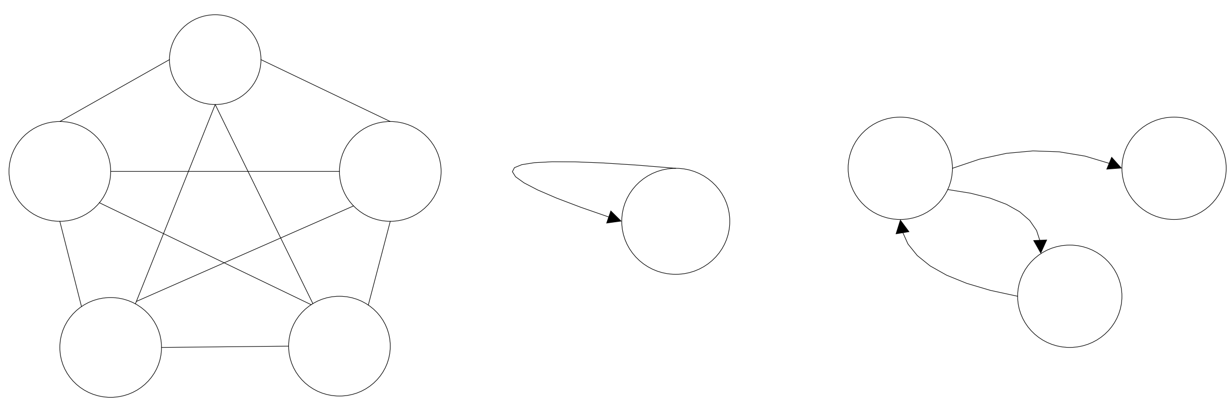


Figure 2.3. Typical graph (left), Loop (middle), Directed graph (right)

The fuzzy complexity graph is a directed graph made up of a crisp set of nodes and a fuzzy set of relations. Generally, let $\tilde{G}(V, \tilde{R})$ be a complexity graph where $V = \{P_1, P_2, ...P_n\}$is a set of nodes representing maintenance projects and $\tilde{R} = \left\{ (P_i \to P_j, \left\| \mu_{P_i \to P_j} \right\|) \middle| P_i \to P_j \subseteq P \times P \right\}$ is a fuzzy set of complexity relations between projects. This complexity graph can be presented by a square matrix $\tilde{M}$ as follows:

$$\tilde{M} = \begin{bmatrix} 0, m_{12}, m_{13}, ...m_{1n} \\ m_{21}, 0, ...m_{2n} \\ . \\ . \\ m_{n1}, m_{n2}, ...0 \end{bmatrix} \tag{2.4}$$

Where $m_{ij} = \left\| \mu_{P_i \to P_j} \right\| \qquad \forall i, j, i \neq j$

To find direct and indirect complexity relations among projects, the expected value of the matrix $\tilde{M}$ denoted by $\tilde{M}'$ can be calculated by

$$\tilde{M}' = lim_{n \to \infty} \tilde{M}^n \tag{2.5}$$

Where $M_{ij}^n = max\{min(m_{ik}, m_{kj}^{n-1}) \quad k = 1,2,...n\} \, \forall i, j$

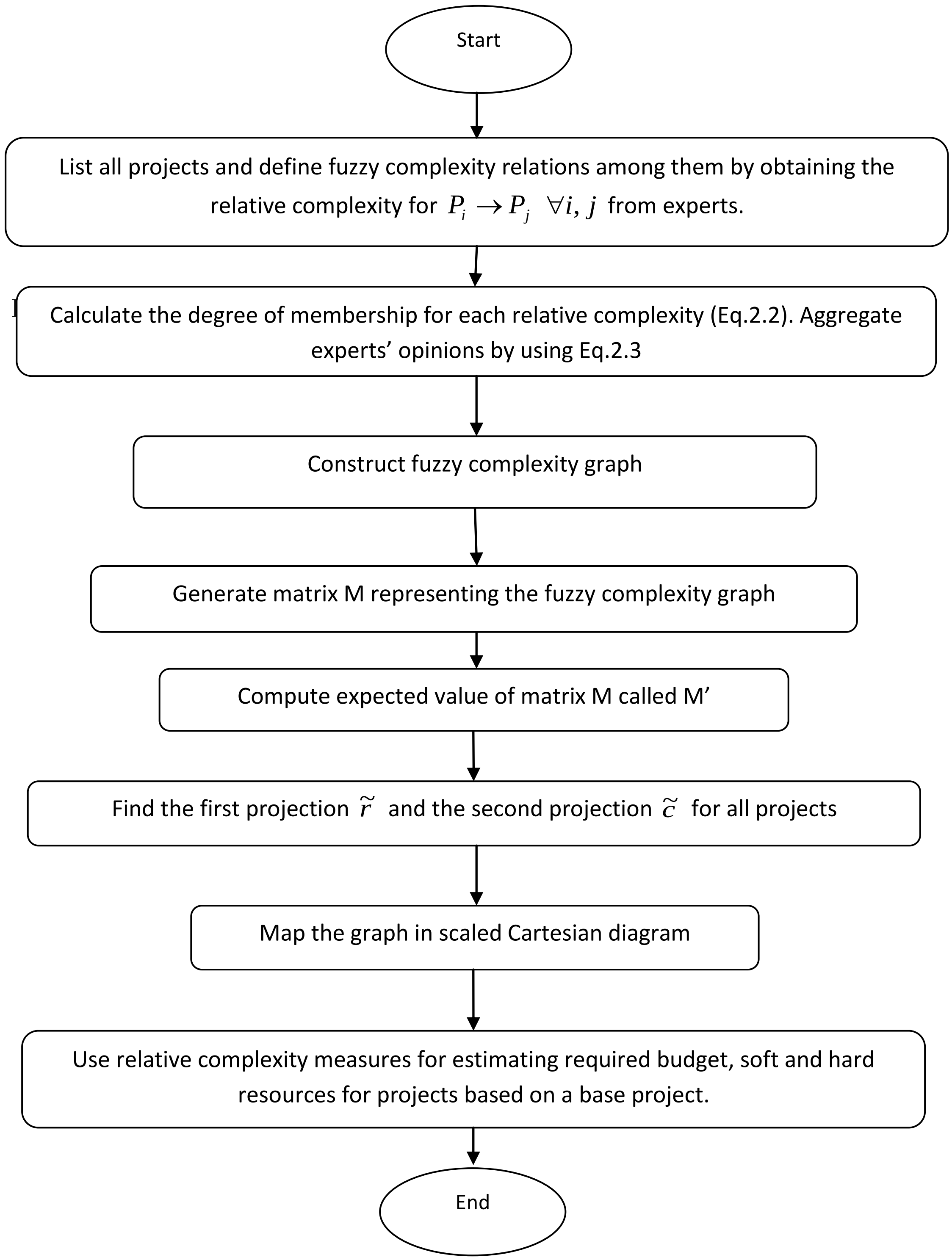
The expected value of matrix $\tilde{M}$ is equal to $\tilde{M}^n$ where $\tilde{M}^n = \tilde{M}^{n+1}$ (i.e., $m_{ij}^n = m_{ij}^{n+1} \quad \forall i, j$) or ranking orders of the projects based on $\tilde{r} / \tilde{c}$ in $\tilde{M}^n$ and $\tilde{M}^{n+1}$ are similar. Using $\tilde{M}'$, the degree of membership of relative complexity of projects denoted by $\tilde{r}$ can be derived by the first projection (Eq. 2.6). Also, the second projection depicts the relaxation $\tilde{c}$ of a project (Eq 2.7).

$$\tilde{r} = \left\{ (P_i \to P_j, \max_{P_j} (m_{ij})) \,\middle|\, P_i \to P_j \subseteq P \times P \quad \forall j \right\} \tag{2.6}$$

$$\tilde{c} = \left\{ (P_i \to P_j, \max_{P_i} (m_{ij})) \,\middle|\, P_i \to P_j \subseteq P \times P \quad \forall i \right\} \tag{2.7}$$

Thus, mapping the complexity graph in $\mu_{(\tilde{c})} \times \mu_{(\tilde{r})}$ Cartesian diagram presents a scaled degree of complexity and of relaxation memberships. Considering the required budget, soft and hard resources for a base project, this scaled graph can be used to estimate budget, soft and hard resources for other projects based on their relative complexity measures (Rodriguez et al., 2003).

In this model, it is assumed a Δ difference in relative complexities of two projects translates to Δ% difference in their budgets.



Figurer 2.4. The fuzzy graph-based algorithm for complexity analysis (Shafiei-Monfared & Jenab,2010a)

2.3 An Illustrative Example

To illustrate the model, a hypothetical example is presented in this section. Consider an enterprise company with five overhaul maintenance projects, which must be managed for aircraft engines with some design variation. These projects require a budget and resources that can be estimated by using the relative complexity of the projects to the base project.

Figure 2.5 shows the complexity graph for these projects that has five nodes representing the projects and fuzzy relations representing relative complexities.

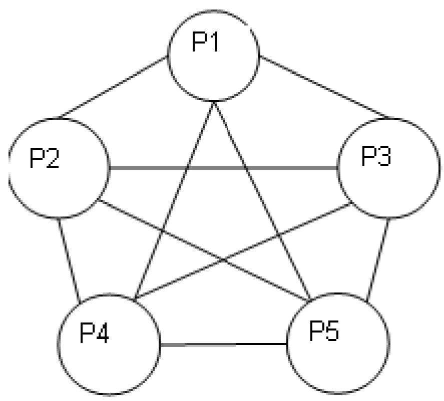


Figure 2.5. Complexity graph

To determine the degrees of membership of the relative complexities, relative complexities among the projects are obtained from three experts. Each expert is asked to determine in what degree project *i* is more complex than project *j* by a value in the range [0-10].

Table 2.1 shows the experts not only do not agree on ranking order of the projects based on complexity measures but also assign different values for the relative complexities among projects. (Appendix-A presents two scenarios for no conflict and some conflict among experts).

	Project	1	2	3	4	5
Expert 1	**1**	0	8	8	10	9
	2	1	0	10	8	0
	3	2	1	0	0	1
	4	0	1	8	0	7
	5	1	10	8	5	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	9	9	10	10
	2	0	0	10	9	1
	3	1	0	0	1	0
	4	0	0	9	0	6
	5	0	9	9	6	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	9	9	9	10
	2	1	0	10	10	1
	3	0	0	0	1	0
	4	0	0	10	0	9
	5	0	10	10	2	0

Table 2.1. Relative complexity among projects obtained from three experts

Using Eq.2.2, the degree of membership for each relative complexity can be calculated (Table 2.2). The degree membership function generates values in the range [0-1].

To mitigate the conflict of experts' opinion on relative complexities, the degree membership values must be aggregated by using Eq.2.3. Table 2.3 presents the relative cardinality membership among projects.

	Project	1	2	3	4	5
Expert 1	**1**	0	0.8	0.8	1	0.9
	2	0.1	0	1	0.8	0
	3	0.2	0.1	0	0	0.1
	4	0	0.1	0.8	0	0.7
	5	0.1	1	0.8	0.5	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	0.9	0.9	1	1
	2	0	0	1	0.9	0.1
	3	0.1	0	0	0.1	0
	4	0	0	0.9	0	0.6
	5	0	0.9	0.9	0.6	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	0.9	0.9	0.9	1
	2	0.1	0	1	1	0.1
	3	0	0	0	0.1	0
	4	0	0	1	0	0.9
	5	0	1	1	0.2	0

Table 2.2. Degree of membership for relative complexity between projects

Project	1	2	3	4	5
1	0	0.867	0.867	0.967	0.967
2	0.067	0	1	0.9	0.067
3	0.1	0.033	0	0.067	0.033
4	0	0.033	0.9	0	0.733
5	0.033	0.967	0.9	0.433	0

Table 2.3. Relative cardinality values representing $m_{ij}\ \forall i, j, i \neq j$ in matrix $\tilde{M}$

Now, the fuzzy complexity graph in Figure 2.5 can be shown by matrix *M* in Table 2.4. Using Eq.2.5, the expected value of matrix *M* must be calculated. In this example, the expected value of matrix *M* can be reached at *n=2* because the ranking orders of projects for n=1 and n=2 are similar. Table 2.5 presents the expected value of matrix *M*. Using *M'* in Table 2.6, the degree of membership of relative complexity for a project complexity denoted by $\tilde{r}$ can be derived by the first projection (Eq. 2.6). The high degree of membership corresponding to a relative complexity for a project means that the project is more complex than other project with respect to technical and managerial aspects. Furthermore, the second projection depicts the relaxation $\tilde{c}$ of a project (Eq. 2.7) which is used for mapping the fuzzy graph and ranking projects.

Project	**1**	**2**	**3**	**4**	**5**	$\tilde{r}$	Ratio $\tilde{r}/\tilde{c}$	**Normalized** $\tilde{r}/\tilde{c}$	**Ranking**
1	0	0.867	0.867	0.967	0.967	0.967	9.67	1	1
2	0.067	0	1	0.9	0.067	1	1.034	1	2
3	0.1	0.033	0	0.067	0.033	0.1	0.1	0.1	5
4	0	0.033	0.9	0	0.733	0.9	0.931	0.096	4
5	0.033	0.967	0.9	0.433	0	0.967	1	0.103	3
$\tilde{c}$	0.1	0.967	1	0.967	0.967				

Table 2.4: Matrix $\tilde{M}$ representing complexity graph

Project	**1**	**2**	**3**	**4**	**5**	$\tilde{r}$	Ratio $\tilde{r}/\tilde{c}$	**Normalized** $\tilde{r}/\tilde{c}$	**Ranking**
1	0.1	0.967	0.9	0.867	0.733	0.967	9.67	1	1
2	0.1	0.067	0.9	0.067	0.733	0.9	0.931	0.705	3
3	0.033	0.1	0.1	0.1	0.1	0.1	0.103	0.0784	5
4	0.1	0.733	0.733	0.433	0.033	0.733	0.814	0.084	4
5	0.1	0.033	0.967	0.9	0.433	0.967	1.319	0.136	2
$\tilde{c}$	0.1	0.967	0.967	0.9	0.733				

Table 2.5: $\tilde{M}'$ – Expected value of matrix $\tilde{M}$

	$\tilde{c}$	$\tilde{r}$	$\tilde{r}/\tilde{c}$	**Normalized** $\tilde{r}/\tilde{c}$	**Ranking**
P1	0.1	0.967	9.67	1	1
P2	0.967	0.9	0.931	0.705	3
p3	0.967	0.1	0.103	0.0784	5
p4	0.9	0.733	0.814	0.084	4
p5	0.733	0.967	1.319	0.136	2

Table 2.6: The first and second projections of matrix $\tilde{M}'$

Based on Table 2.6, Figure 2.6 shows the mapped scaled Cartesian diagram that indicates maintenance project 1 is the most complex project in terms of both managerial and technical aspects. Also, project 3 and 4 are the least complex projects. Since the first projection values for projects 3 and 4 are similar, normalized $\tilde{r}/\tilde{c}$ can be used for ranking projects 3 and 4. Assuming required budget and resources for the maintenance project 3 are known, the required budget and resources for the other projects can be estimated by using their relative complexity. For example, in Figure 2.7, the relative complexities for the degrees of membership of projects 1 and 3 are 9.67 and 0.1 that are corresponding to the degrees of membership 0.967 and 0.1 for projects 1 and 3, respectively. Thus, the coefficient factor, Δ, is 1 in scale 1 to 10, which means 87% difference between relative complexities of projects 1 & 3 can be translated to 87% difference in their budgets and resources.

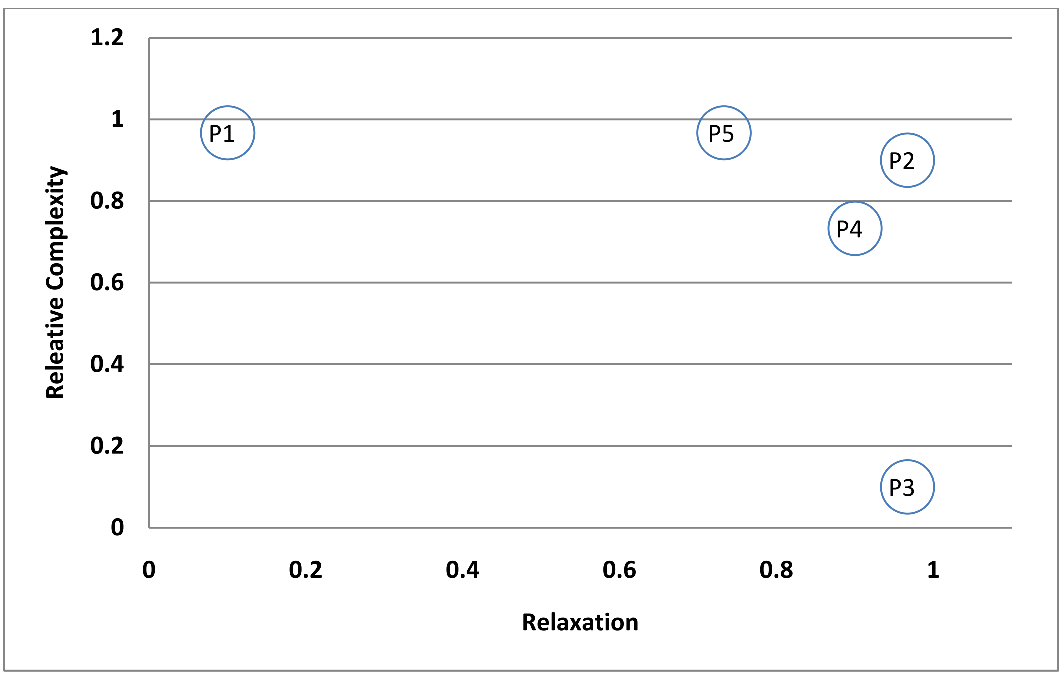


Figure 2.6. Mapped complexity graph on $\mu_{(\tilde{c})} \times \mu_{(\tilde{r})}$ axes

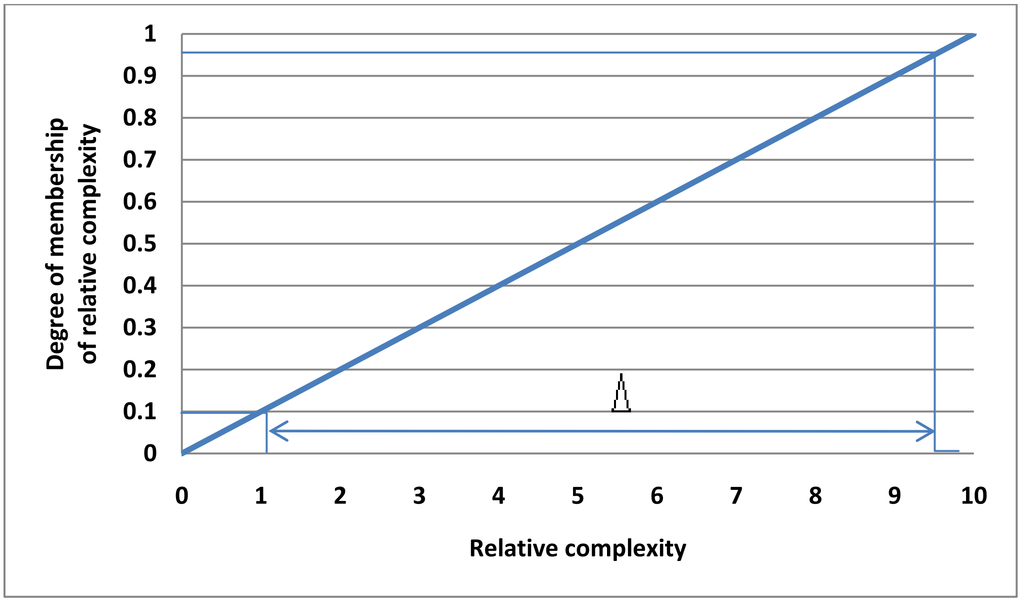


Figure 2.7. Coefficient factor curve

2.4 Conclusions

The complexity of maintenance projects can be investigated through technical and managerial aspects of projects. However, these aspects may not be measured precisely due to uncertain situations or the lack of information. Therefore, a fuzzy graph-based model is proposed to evaluate the relative complexity of maintenance projects. The complexity measure can be used as a yardstick to estimate the required budget and resources for projects based on the known budget and resource of a base project. The proposed model collects fuzzy information from experts and uses conflict resolution operator to dilute their opinions on the relative complexity of projects. Having the degrees of complexity membership function, the relative complexity relations can be presented by a graph and alternatively by a Complexity Design Structure Matrix (CDSM). The model employs a pseudo factor (relaxation) in order to map the graph into a scaled Cartesian diagram for better pictorial view of the complexity relations. Having the degrees of relative complexity, one is able to calculate the coefficient factor that may be used as a yardstick for estimating the budget and resources of a project in comparison with the base project. This model may be improved by utilizing a multi-layer graph whereby each layer represents one aspect of complexity. Further, interrelation between the layers will help in better analyzing the influence of various aspects of complexity of a project.

In the next chapter, a learning curve model is developed that takes into account human cognition and task complexity as influential factors in TTR. The maintenance learning curve is made up of two segments that join at a breakpoint time. The breakpoint indicates the required number of trials in order to reach mastery level for performing a certain task unsupervised. As a result, complexity of a task can be derived from the learning curve.

Chapter 3

Human cognitive and complexity analyses in maintenance

3.1 Background

Learning curves have been receiving an increasing attention by researchers and practitioners for almost seven decades (Yelle, 1979). The earliest learning curve is a geometric progression that expresses the decreasing time required to accomplish any repetitive operation. The theory in its general form states that as the total quantity of units produced doubles, the time per unit declines by some constant percentage. However, the form of the learning curve has been debated by many researchers and practitioners, by far, the Wrights learning curve (WLC) is the most widely used model (Yelle, 1980; Jaber & Guiffrida, 2004). Assuming a perfect system, the WLC shows that the time required to accomplish a repetitive task decreases with each subsequent repetition. In 2010, lot splitting in a serial production, Jaber & Khan (2010) proposed a learning curve for imperfect system with rework and scrap. Badiru (1992) classified existing univariate models as follows:

- The log-linear model (Wright, 1936)
- The Stanford-B model (Asher, 1956)
- DeJong’s learning formula (DeJong, 1957)
- Levy’s adaptation function (Levy, 1965)
- Pegel’s exponential function (Pegels, 1969)

- Knecht's upturn model (Knecht, 1974)
- Yelle's product model (Yelle, 1976)
- Multiplicative power model (Waller & Dwyer, 1981)

The power function fit appears to be robust regardless of the methods used (Rosenbloom & Newell, 1987). However, Heathcote et al., (2000) suggest that the power law might be an artefact arising from averaging proposed by Anderson & Tweney, (1997). Also, the exponential function may be the best fit when individual subjects employing a single strategy. Differentiation between the power and exponential functions is not just an exercise in equation fitting. If learning process follows an exponential curve, then learning is based on a fixed percentage of what remains to be learnt. On the other hand, if learning process follows a power law, then learning slows down.

In a wide variety of systems, automation is a significant substitution of mechanical, electrical, or computerized action for human effort. However, automation has a limited application in maintenance systems because of the impact of human intelligence in diagnoses and repairs. Also, call on maintenance is stochastic processes that may not be fitted into traditional learning curve models. Moreover, complexity of a maintenance project is another influential factor in time to repair that is not quantified. In this chapter, human cognition and complexity factors in maintenance projects are studied. Performing statistical analysis, a new learning curve is developed that is a best fit for time to repair curve with breakpoint feature. The breakpoint indicates the required number of trials in order to reach mastery level of performing a certain task, unsupervised. Using collected data from a jet engine manufacturer, a comparative analysis among existing and the newly developed models is performed and complexity measure is derived from the model.

3.2 Human Cognitive and Complexity Analysis in Maintenance

To study the effects of human cognition and task complexity as two influential factors, factorial design method is used. This method can analyze all possible combinations of the levels of the factors. In this analysis, maintenance experts' opinions are used to define the level of complexity (None, Low, Medium, and High) and of human cognition (Low, Medium, High) for twelve maintenance tasks performed by three maintenance technicians. Table 3.1 presents the time to repair in hour for these tasks.

Human Cognitive	Complexity			
	None:1	Low:2	Medium:3	High:4
1: Low	7.4	7.9	8.2	9.9
	6.4	6.8	8.8	10.4
	6	7.3	9.2	9.6
2: Medium	9.2	9.8	9.9	10.4
	8.6	10.4	10.8	11
	8.8	8.8	9.5	9.9
3: High	9.9	10.4	10.8	11.4
	9.8	9.9	11	11.1
	10.2	9.5	9.9	10.7

Table 3.1. Time to repair (in hours) data considering human cognitive and complexity factors

The effect of a factor is defined as the change in response produced by a change in the level of the factor. This is frequently called a main effect because it refers to the primary factors of interest in the experiment. In Table 3.1, the experiment is designed for time to repair (TTR) that will be subject to some variations in both human cognition and task complexity. By performing factorial design analysis, the effect of complexity and human cognitive abilities on the TTR can be studied. Table 3.2 shows the result of the analysis of variance (ANOVA). The ANOVA table shows how the sum of squares (SS) is partitioned into the four components. Calculation steps are shown in Appendix-B. For each component, the table shows sum-of-squares (SS), degrees of freedom (df), mean square (MS), P-value, and F values. Each F value is the ratio of the mean-square value for that source of variation to the residual mean square (with repeated-measures ANOVA, the denominator of one F ratio is the mean square for matching rather than α. In Table 3.2, the P-Values are less than α=0.05. Therefore, it is concluded that the human cognitive abilities and task complexity influences on TTR are significant. In next section, the complexity measure of a maintenance task by developing a new learning curve, which takes into account human cognitive abilities in performing a certain task, is investigated.

Source of Variation	SS	df	MS	F	P-value	F
Sample	10683.72	2	5341.861	7.911372	0.001976	3.354131
Columns	39118.72	2	19559.36	28.96769	1.91E-07	3.354131
Interaction	9613.778	4	2403.444	3.559535	0.018611	2.727765
Within	18230.75	27	675.213			
Total	77646.97	35				

Table 3.2. The result of ANOVA

3.3 Complexity Analysis in Maintenance

A number of learning curve models have been used to reflect the fact that workers often requires less time to perform a complex task after they acquires some familiarity and experience with the task (Bailey & McIntyre, 1992). In literature, the exponential, logarithmic, and power low learning curves seem to be suitable models for human behaviour in the learning process. However, these models may not be applicable to maintenance tasks, which not only occurs in a random and very long interval but also requires human cognitive abilities. For example, the number of failures for ten pumps is reported in Table 3.3.

Assuming the total number of call for maintenance is fitted in Poisson distribution, the common λ can be calculated. As the total number of call is 75 within 305.4 months, the common call rate is 0.246. Although the common call rate across pumps is not warranted, it is assumed that it is the case.

Therefore, it is expected to observe one pump failure in every four months. This long period does not allow maintenance crew to have opportunity for learning the maintenance procedure as quickly as repetitive jobs in manufacturing processes.

Pump	1	2	3	4	5	6	7	8	9	10
No. of maintenance call	5	1	5	14	3	19	1	1	4	22
Time (month) (t_i)	94.32	15.72	62.88	125.76	5.24	31.44	1.05	1.05	2.10	10.48
λ	.053	.064	.080	.111	.573	.604	.952	.952	1.904	2.099

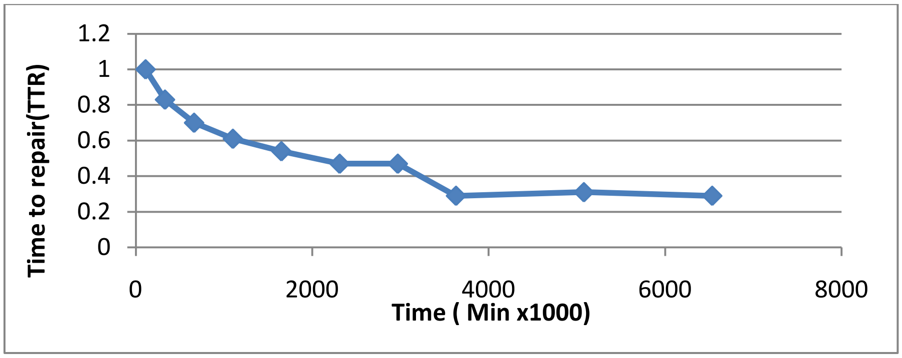
Table 3.3. Pump failure data

Further, the complexity of a maintenance task is an influential factor in learning curve that existing models have paid a little attention to this factor. Complexity in maintenance is generally considered in relation to technical, managerial and human learning aspects. To analyze complexity impact, TTRs for three levels of complexity have been collected in Table 3.4.

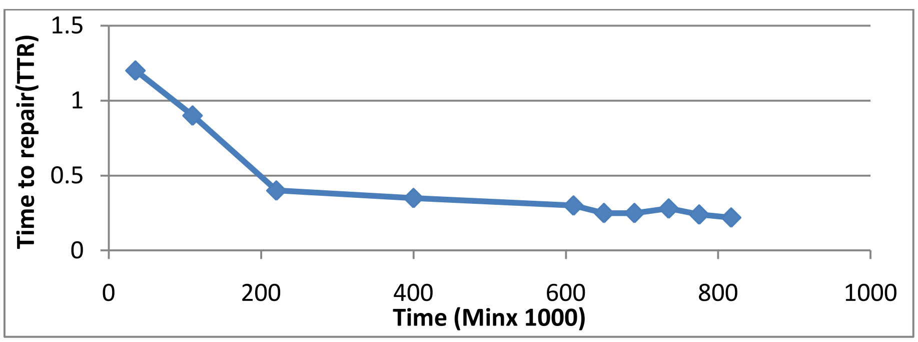
Complexity level	n	TTR	Time (T)	Complexity level	n	TTR	Time (T)	Complexity level	n	TTR	Time (T)
Low	1	1.14	102	Medium	1	1.2	35	High	1	1	110
	2	.71	274		2	0.9	110		2	.83	330
	3	.72	526		3	0.4	220		3	.70	660
	4	.68	608		4	0.35	400		4	.61	1100
	5	.66	692		5	0.3	610		5	.54	1650
	6	.69	824		6	0.25	650		6	.47	2310
	7	.64	906		7	0.25	690		7	.47	2970
	8	.65	999		8	0.28	735		8	.29	3630
	9	.64	1094		9	0.24	775		9	.31	5080
	10	.65	1184		10	0.22	817		10	.29	6535

Table 3.4. TTR (hr) of maintenance tasks with three levels of complexity (Time in Min×1000)

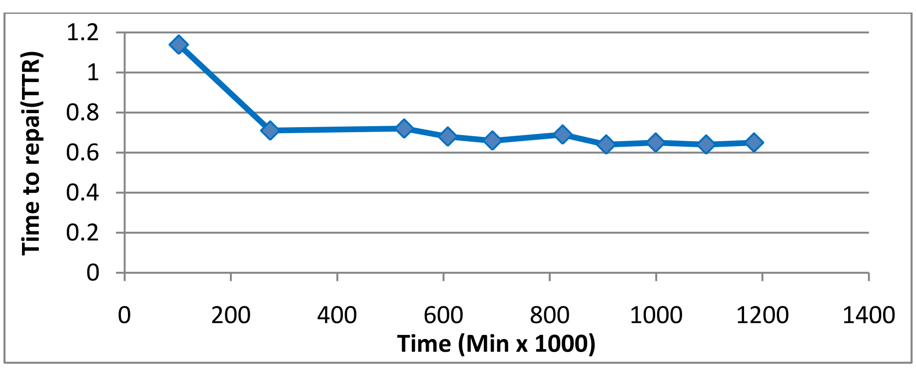
In Table 3.4, the number of collected data is denoted by ‘n’ and the time of failure (i.e., call for maintenance) is shown by ‘T’. By fitting learning curves, Figure 3.1 presents the learning behaviour of the maintenance crew measured by TTR for three complexity levels of maintenance tasks. As shown in Figure 3.1, number of trials to reach the breakpoints is increased by complexity. For example, numbers of trials for low, medium, and high complex tasks are 3, 5, and 8, respectively.



High



Medium



Low

Figure 3.1. TTR (hr) v.s. Service time (Min ×1000)

Considering medium complexity data, the corresponding curve demonstrates that at first it takes maintenance crew about 1.2 hour to diagnose, repair and restore the system. However, after the fifth iteration, the maintenance crew learns how to do the task without losing time. As a result, the curve shows a constant trend after the sixth iteration.

In general, the learning curve for a maintenance task that requires human cognitive is made up of two segments (exponential curve and constant linear segments).

The first segment represents the learning period, which is an exponential curve. This segment joins to a linear segment at breakpoint that represents constant TTR as shown in Figure 3.2.

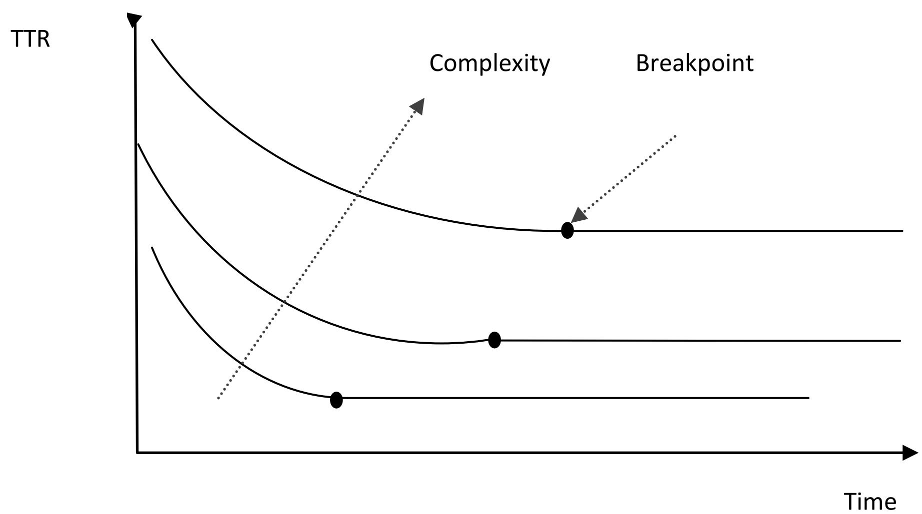


Figure 3.2. TTR curves based on complexity levels

Considering cognitive value (β) is depended on the breakpoint time, this curve is defined as follows (Shafiei-Monfared & Jenab, 2010b):

$$TTR = \begin{cases} \dfrac{\beta}{\alpha^{\beta}} e^{-\left(\frac{t}{\alpha}\right)^{\beta-1}} t^{\beta-1} & t < t_0 \\ \dfrac{\beta}{\alpha^{\beta}} e^{-\left(\frac{t_0}{\alpha}\right)^{\beta-1}} t_0^{\beta-1} & t \geq t_0 \end{cases} \tag{3.1}$$

Where α is scale parameter, t represents time, and t_0 denotes breakpoint time.

To estimate the cognitive factor, β, and scale parameter, α, the SSE values of the best fitted curves must be compared.

By moving breakpoint from the first occurrence to the next one, the β and α for Eq.3.1 can be estimated by RARE© software. For computational purpose, visual inspection of the learning curve can help in finding the breakpoint time.

In this case study, the cognitive factor varies between 0.5 to 1 before breakpoint while it varies between 1 to 1.25 after the breakpoint.

For example, the cognitive factors for high, medium, and low complex tasks are 1.25, 0.7, and 0.5. As a result, the breakpoint of the task with low complexity occurs early.

The breakpoint of a high complex task occurs at more iteration. Also, the breakpoint of the medium complexity task is between high and low complex ones (i.e., $0.5 < \beta < 1.25$).

To evaluate the performance of the current model, a comparative analysis among existing models (exponential, logarithmic, and power) is performed.

The results shown in Figures 3.3-5 indicate that the current model is slightly better in terms of SSE value. For a high complex task, the SSE values for exponential, logarithmic, and power leaning curves are 0.875, 0.9759, and 0.9074. However, the SSE of the current model is 0.7807 (Details presented in Appendix C).

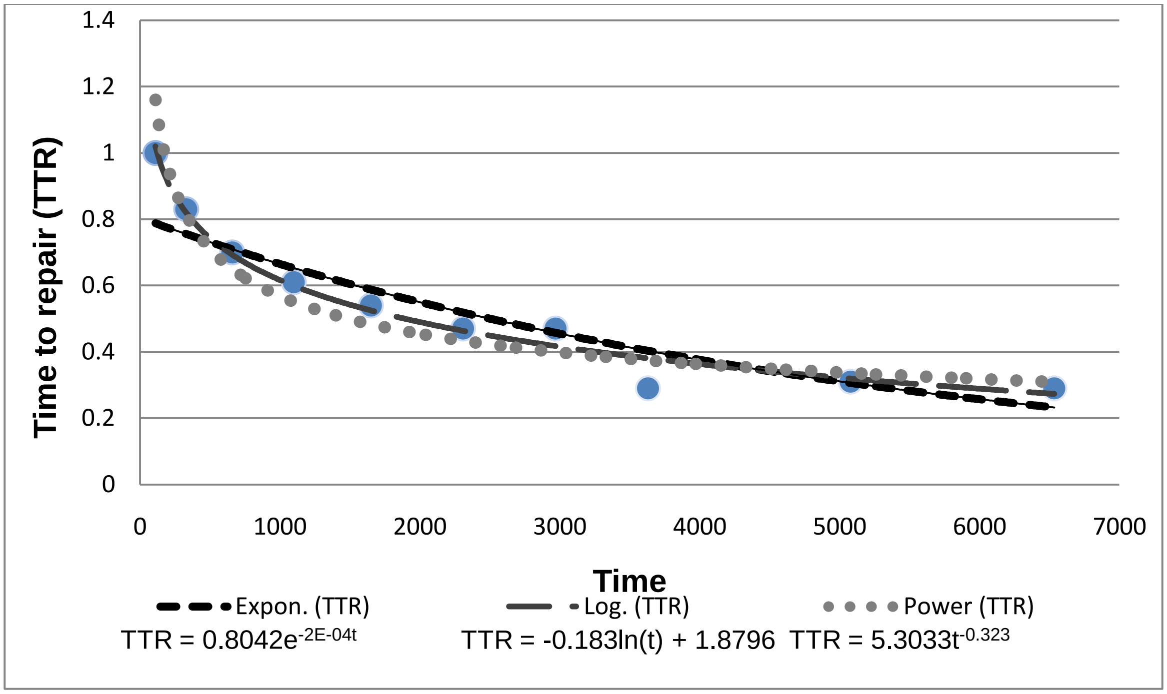


Figure 3.3. The best fit exponential, logarithmic and power law in high complex task.

As depicted in Figure 3.4 for a medium complex task, SSE values for exponential, logarithmic and power models are 0.8604, 0.943, and. 0.9564. The SSE value for the current model is 0.1138.

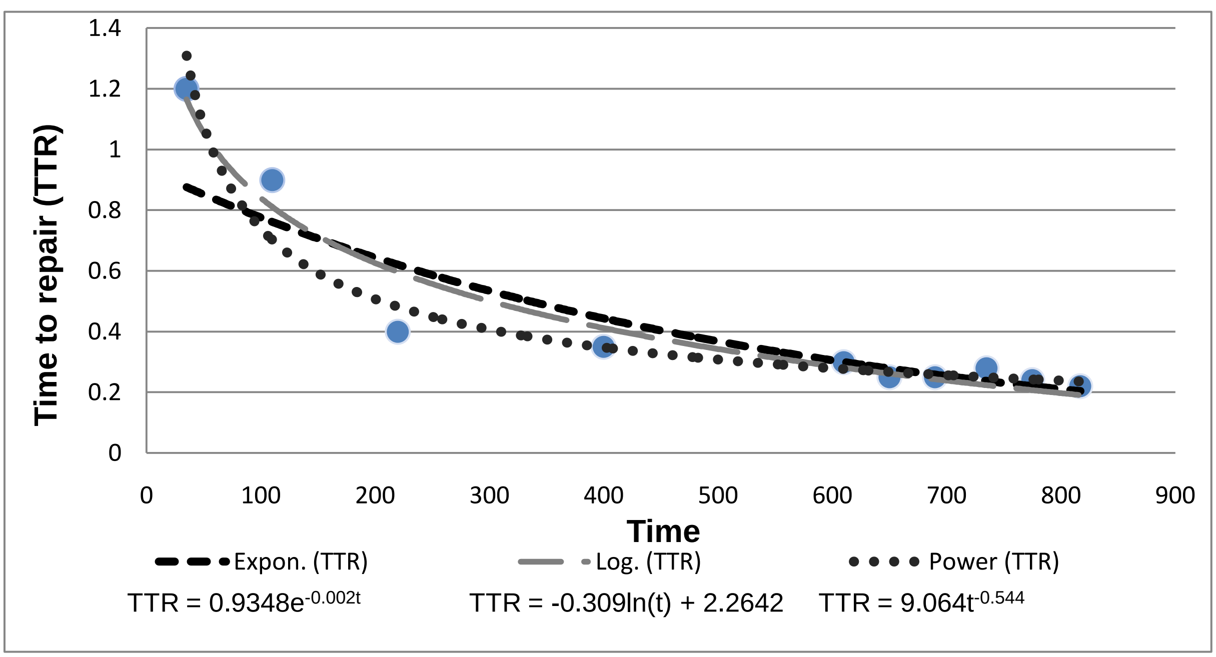


Figure 3.4. The best fit exponential, logarithmic and power law in medium complex task.

Considering a medium complex task, the SSE values for exponential, logarithmic, and power learning curves are 0.5762, 0.8006, and 0.8278. On the other hand, the SSE of the current model is 0.3058 as presented in Figure 3.4.

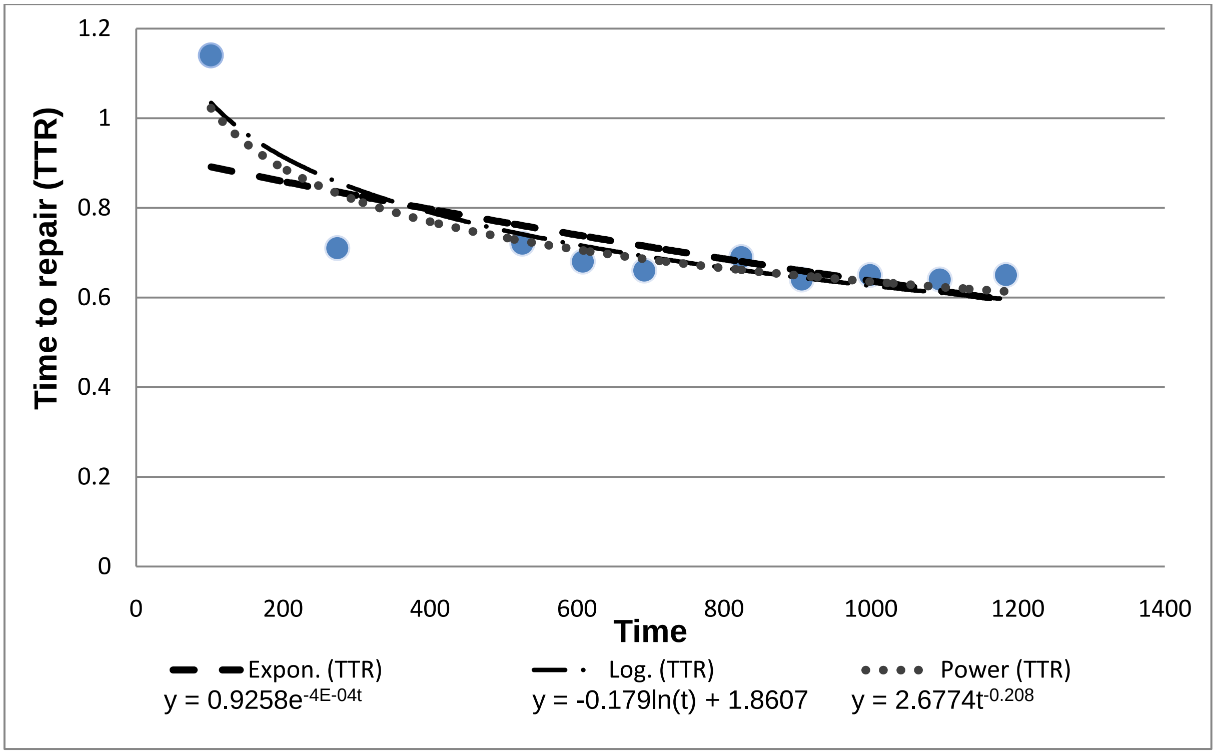


Figure 3.5. The best fit exponential, logarithmic and power law in low complex task.

The results of this comparative analysis among models for different levels of complexity prove that the newly developed model is slightly better than other learning curve models for maintenance tasks. Because complexity of a task has direct relation to its breakpoint time in learning curves, a task's complexity can be derived from Eq.3.1. Having the time of the occurrence of the breakpoint denoted by t_0, the complexity is expressed by

$$CP = 1 - e^{-(\frac{t_0}{\alpha})^{\beta}} \tag{3.2}$$

Considering a task performed by a standard worker, the time of a breakpoint in *CP* curve indicates the task's complexity. For example, the *CP* curves of three tasks are presented in Figure 3.6 that each one has different level of complexity.

The breakpoint on the high complexity curve labelled by β=0.9 occurs later than the breakpoints on the medium and low complexity curves. For example, the complexity levels of the tasks shown in Figure 3.2 are 0.51, 0.52, and 0.95 for low, medium, and high levels as depicted in Figure 3.6

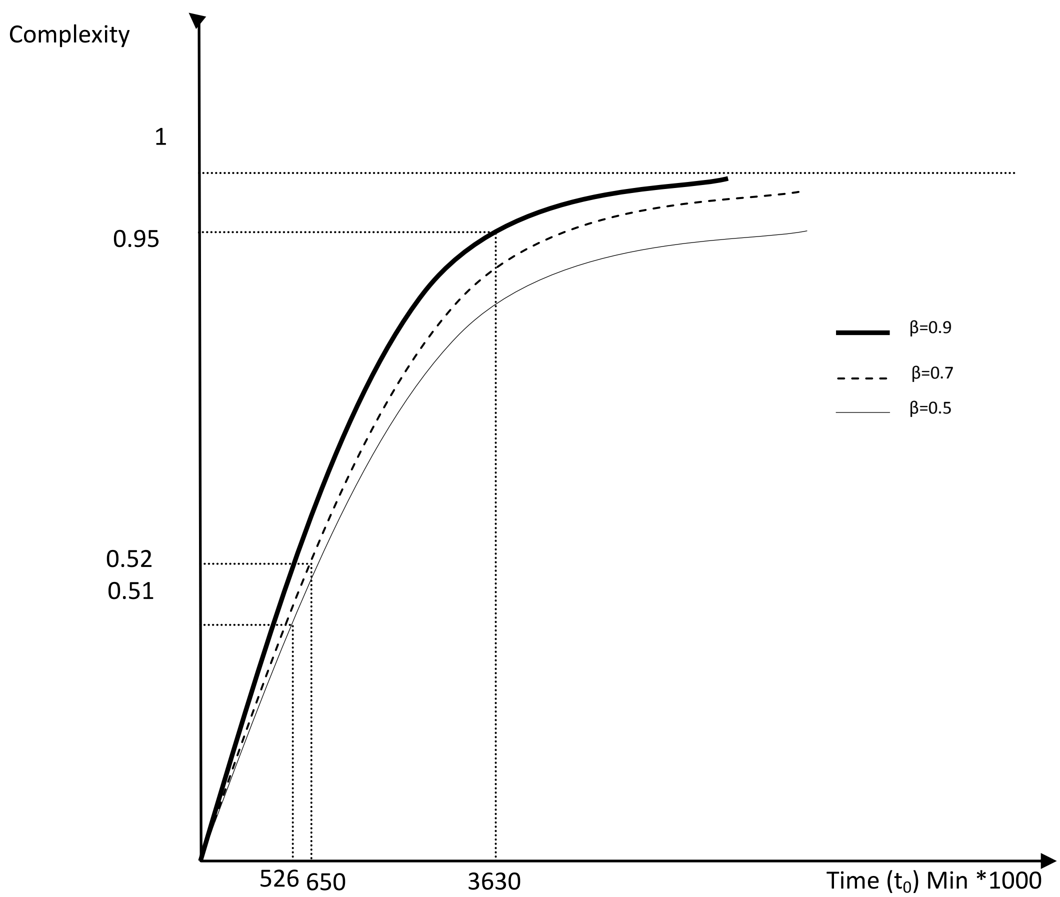


Figure 3.6. The complexity curves

3.4 Conclusions

In this Chapter, the impact of human cognitive and task complexity in maintenance is studied. Performing statistical analysis indicates that these factors are significant. Also, a maintenance task occurs in a random and very long interval that results in a longer learning period. As a result, the learning curves in the pertained literature not only may not be suitable for maintenance tasks but also cannot provide complexity measure of a task. Therefore, a new learning curve is developed that is composed of two segments. The first segment is an exponential curve that reflects the fact that the maintenance crew generally require less time to perform a task after they acquires some familiarity and experience with the task. The exponential segment is connected to linear segment that shows TTR is almost constant after the breakpoint time. The newly developed learning curve model has two parameters α and β that are scale and human cognitive abilities parameters. The value of β varies between 0 to 1.25 where the bigger value means a more complex task. The complexity of a task can be derived from the learning curve model at the breakpoint time by using Eq.3.2. Further application of this model is in demand-based manufacturing systems such as job shop with lot size 1 where orders arrive randomly in a long time interval. This model would be further investigated for uncertain situations.

Chapter 4

Conclusions and future research

This thesis reports two models for quantifying the complexity of the projects in maintenance systems. The complexity of a project can be used as a yardstick to estimate the required resources and budget for a project based on the other one.

In maintenance projects, the complexity can be investigated through technical and managerial aspects of the projects. However, these aspects may not be measured precisely because of uncertain situations or the lack of information. Therefore, a fuzzy graph-based model is proposed to evaluate the relative complexity of maintenance projects. The proposed model collects fuzzy information from experts and uses conflict resolution operator to dilute their opinions on the complexity of the projects. Having the degrees of complexity membership function, the relative complexity relations can be presented by a graph and alternatively by a CDSM. The model employs a pseudo factor (relaxation) in order to map the graph into a scaled Cartesian diagram for better pictorial view of the complexity relations. This model may be improved by utilizing a multi-layer graph whereby each layer represents one aspect of complexity. Further, interrelation between the layers will help in analyzing the influence of various aspects of complexity in a project.

Also, the impact of human cognition and task complexity in maintenance is studied. Performing statistical analysis indicates that these factors are significant. A maintenance task occurs in a random and very long interval that results in longer learning period. As a result, the learning curves in related literature not only may not be suitable to maintenance tasks but also cannot provide complexity measure for tasks. Therefore, a new learning curve is developed that is composed of two segments. The first segment is an exponential curve that reflects the fact that maintenance crews generally require less time to perform a task after they acquire some familiarity and experience with the task. The exponential segment is connected to linear segment that shows TTR is almost constant after the breakpoint. The newly developed learning curve model has two parameters α and β that are scale and human cognitive abilities parameters. The value of β varies between 0 to 1.25 where the bigger value means a more complex task. The complexity of a task can be derived from the learning curve model at the breakpoint time. Also, the model can apply in manufacturing systems such as job shop where lot size is 1 and orders arrive randomly in a long time interval. For future work, one can adapt this model for type-2 fuzzy sets. Type 2 fuzzy sets provides more uncertainty because it incorporates uncertainty about the membership function for fuzzy relative complexity. The membership function of a general type-2 fuzzy set is composed of three-dimensions. The third dimension is the value of the membership function at each point on its two-dimensional domain that is called footprint of uncertainty.

Appendix-A

Scenario I: Consider the hypothetical example presented in Section 2.3. In scenario I, it is assumed there is no conflict among experts on ranking order of the projects with respect to their complexity. Also, there is no disagreement on relative complexity values.

	Project	1	2	3	4	5
Expert 1	**1**	0	10	10	10	10
	2	4	0	10	10	0
	3	0	1	0	10	1
	4	0	0	0	0	0
	5	0	9	9	10	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	10	10	10	10
	2	4	0	10	10	0
	3	0	1	0	10	1
	4	0	0	0	0	0
	5	0	9	9	10	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	10	10	10	10
	2	4	0	10	10	0
	3	0	1	0	10	1
	4	0	0	0	0	0
	5	0	9	9	10	0

Table A.1. Scenario I: Relative complexity among projects obtained from three experts

	Project	1	2	3	4	5
Expert 1	**1**	0	1	1	1	1
	2	0.4	0	1	1	0
	3	0	0.1	0	1	0.1
	4	0	0	0	0	0
	5	0	0.9	0.9	1	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	1	1	1	1
	2	0.4	0	1	1	0
	3	0	0.1	0	1	0.1
	4	0	0	0	0	0
	5	0	0.9	0.9	1	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	1	1	1	1
	2	0.4	0	1	1	0
	3	0	0.1	0	1	0.1
	4	0	0	0	0	0
	5	0	0.9	0.9	1	0

Table A.2. Scenario I: Degree of membership for relative complexity between projects

Project	1	2	3	4	5
1	0	1	1	1	1
2	0.4	0	1	1	0
3	0	0.1	0	1	0.1
4	0	0	0	0	0
5	0	0.9	0.9	1	0

Table A.3. Scenario I: Relative cardinality values representing $m_{ij}\ \forall i, j, i \neq j$ in matrix $\tilde{M}$

Project	1	2	3	4	5	$\tilde{r}$	Ratio $\tilde{r}/\tilde{c}$	**Normalized** $\tilde{r}/\tilde{c}$	Ranking
1	0	1	1	1	1	1	2.5	1	4
2	0.4	0	1	1	0	1	1	1	1
3	0	0.1	0	1	0.1	1	1	1	5
4	0	0	0	0	0	0	0	0	3
5	0	0.9	0.9	1	0	1	1	0.4	2
$\tilde{c}$	0.4	1	1	1	1				

Table A.4. Scenario I: Matrix $\tilde{M}$ representing complexity graph

Project	1	2	3	4	5	$\tilde{r}$	Ratio $\tilde{r}\,/\,\tilde{c}$	**Normalized** $\tilde{r}\,/\,\tilde{c}$	**Ranking**
1	0.4	0.9	1	1	0.1	1	2.5	1	4
2	0	0.4	0.4	1	0.4	1	1.11	0.494	1
3	0.1	0.1	0.1	0.1	0	0.1	0.1	0.044	5
4	0	0	0	0	0	0	0	0	3
5	0.4	0.1	0.9	0.9	0.1	0.9	2.25	1	2
$\tilde{c}$	0.4	0.9	1	1	0.4				

Table A.5. Scenario I: $\tilde{M}'$ – Expected value of matrix $\tilde{M}$

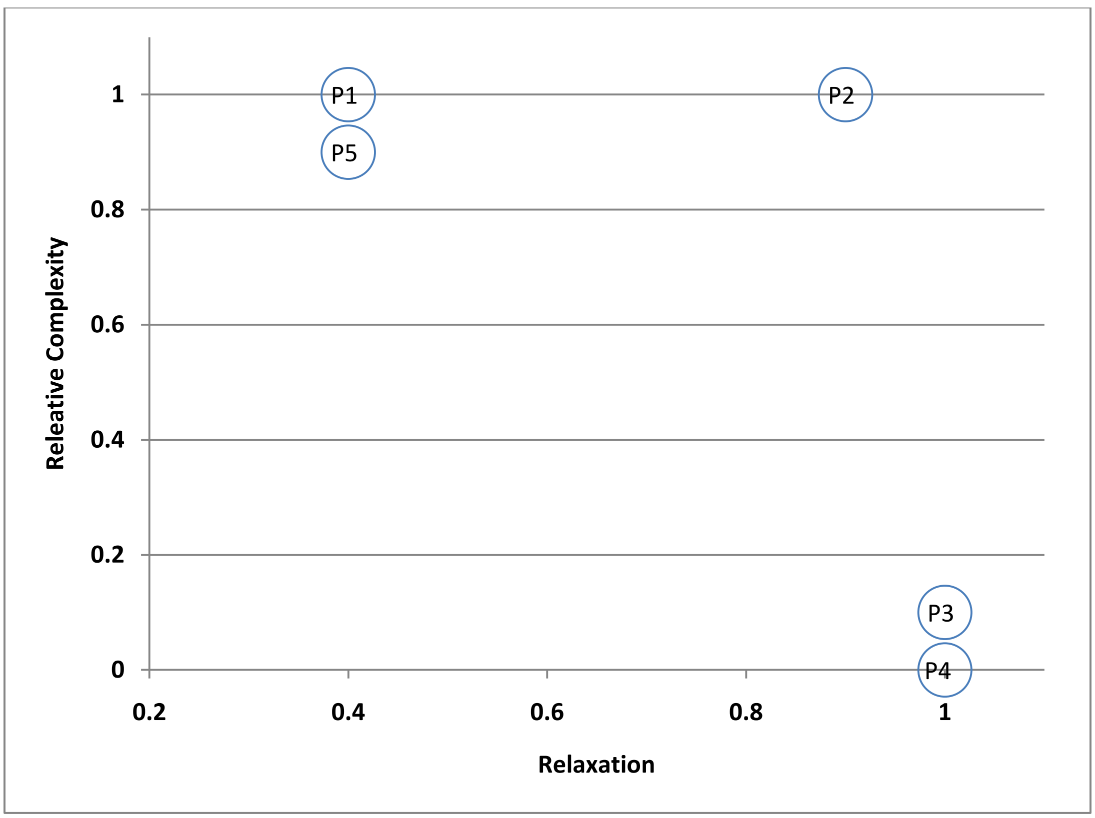


Figure A.1. Scenario I: Mapped complexity graph on $\mu_{(\tilde{c})} \times \mu_{(\tilde{r})}$ axes

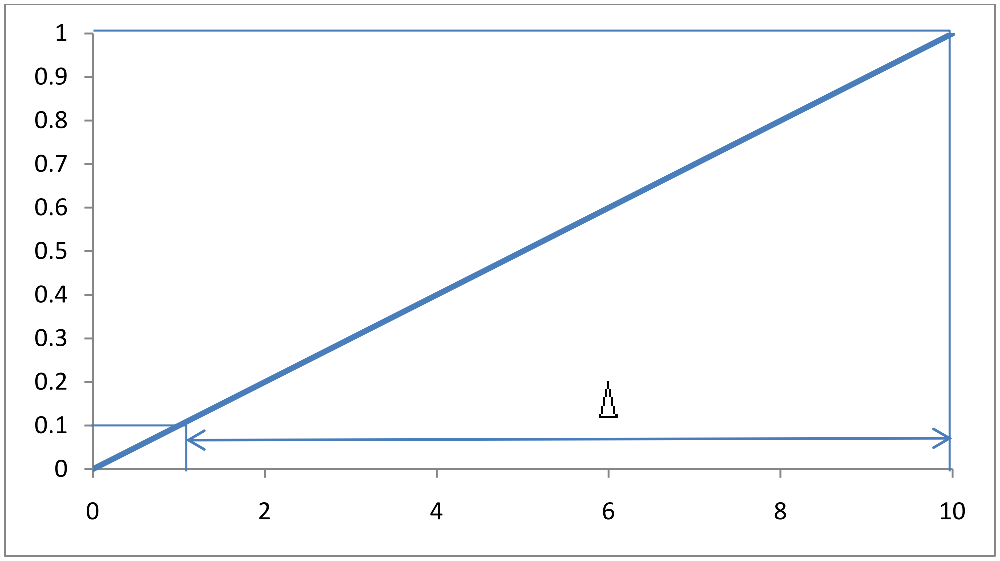


Figure A.2. Scenario I: Coefficient factor curve

For example, the required resources for project 1 is 90% more than those of project 3 (Δ= 0.9).

Scenario II: Consider the hypothetical example presented in Section 2.3. In scenario II, it is assumed experts have inconsistence opinions on the ranking order of the projects with respect to their complexity and the level of relative complexities.

	Project	**1**	**2**	**3**	**4**	**5**
Expert 1	**1**	0	8	3	5	9
	2	4	0	10	9	0
	3	8	3	0	5	1
	4	6	3	5	0	5
	5	2	5	7	7	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	6	5	5	9
	2	2	0	10	9	1
	3	5	0	0	1	1
	4	6	2	9	0	5
	5	5	5	9	8	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	4	4	7	5
	2	5	0	9	8	1
	3	7	0	0	1	3
	4	6	1	8	0	5
	5	4	5	8	6	0

Table A.6. Scenario II: Relative complexity among projects obtained from three experts

	Project	1	2	3	4	5
Expert 1	**1**	0	0.8	0.3	0.5	0.9
	2	0.4	0	1	0.9	0
	3	0.8	0.3	0	0.5	0.1
	4	0.6	0.3	0.5	0	0.5
	5	0.2	0.5	0.7	0.7	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 2	**1**	0	0.6	0.5	0.5	0.9
	2	0.2	0	1	0.9	0.1
	3	0.5	0	0	0.1	0.1
	4	0.6	0.2	0.9	0	0.5
	5	0.5	0.5	0.9	0.8	0
	Project	**1**	**2**	**3**	**4**	**5**
Expert 3	**1**	0	0.4	0.4	0.7	0.5
	2	0.5	0	0.9	0.8	0.1
	3	0.7	0	0	0.1	0.3
	4	0.6	0.1	0.8	0	0.5
	5	0.4	0.5	0.8	0.6	0

Table A.7. Scenario II: Degree of membership for relative complexity between projects

Project	1	2	3	4	5
1	0	0.6	0.4	0.567	0.767
2	0.367	0	0.967	0.867	0.067
3	0.667	0.1	0	0.233	0.167
4	0.6	0.2	0.733	0	0.5
5	0.367	0.5	0.8	0.7	0

Table A.8. Scenario II: Relative cardinality values representing $m_{ij}\ \forall i, j, i \neq j$ in matrix $\tilde{M}$

Project	1	2	3	4	5	$\tilde{r}$	Ratio $\tilde{r} / \tilde{c}$	**Normalized** $\tilde{r} / \tilde{c}$	Ranking
1	0	0.6	0.4	0.567	0.767	0.767	1.150	0.714	2
2	0.367	0	0.967	0.867	0.067	0.967	1.612	1.000	1
3	0.667	0.1	0	0.233	0.167	0.667	0.690	0.428	5
4	0.6	0.2	0.733	0	0.5	0.733	0.845	0.525	4
5	0.367	0.5	0.8	0.7	0	0.8	1.043	0.647	3
$\tilde{c}$	0.667	0.6	0.967	0.867	0.767				

Table A.9. Scenario II: Matrix $\tilde{M}$ representing complexity graph

Project	1	2	3	4	5	$\tilde{r}$	Ratio $\tilde{r}\,/\,\tilde{c}$	**Normalized** $\tilde{r}\,/\,\tilde{c}$	Ranking
1	0.567	0.5	0.767	0.7	0.5	0.767	1.150	0.941	2
2	0.667	0.367	0.733	0.367	0.5	0.733	1.222	1.000	1
3	0.233	0.6	0.4	0.567	0.667	0.667	0.869	0.712	5
4	0.667	0.6	0.5	0.567	0.6	0.667	0.953	0.780	4
5	0.667	0.367	0.7	0.5	0.5	0.7	1.049	0.859	3
$\tilde{c}$	0.667	0.6	0.767	0.7	0.667				

Table A.10. Scenario II: $\tilde{M}'$ – Expected value of matrix $\tilde{M}$

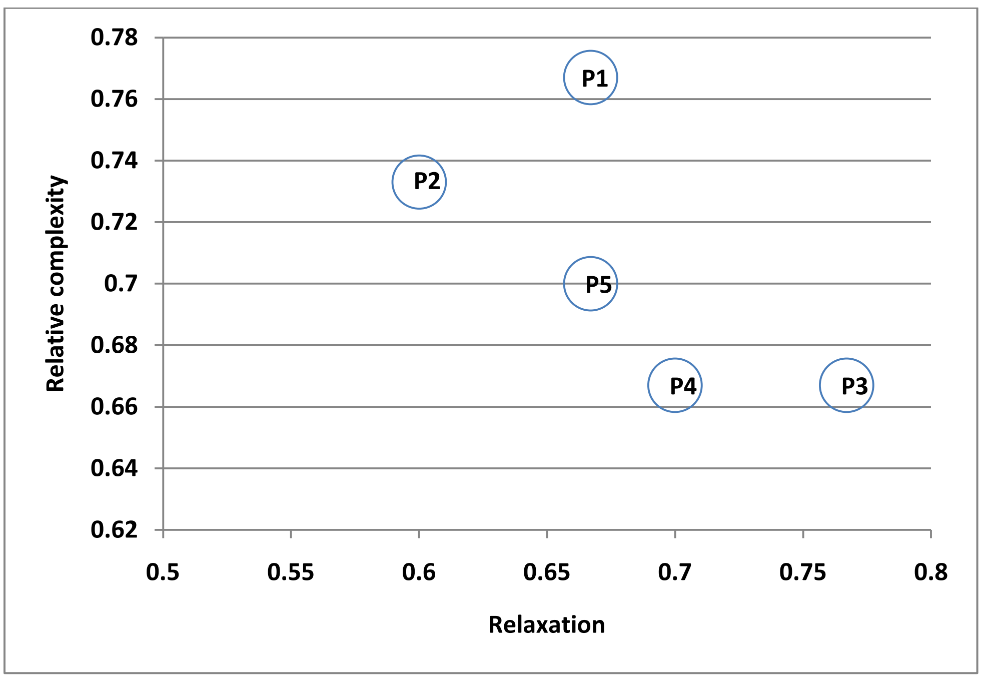


Figure A.3. Scenario II: Mapped complexity graph on $\mu_{(\tilde{c})} \times \mu_{(\tilde{r})}$ axes

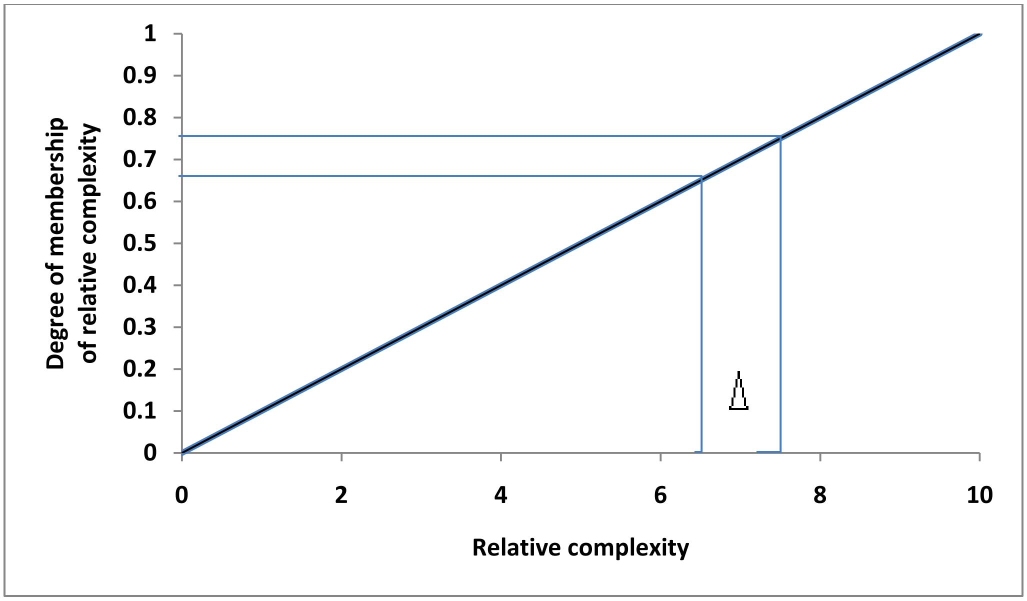


Figure A.4. Scenario II: Coefficient factor curve

For example, the required resources for project 1 is 10% more than those of project 3 (Δ=0.1).

Appendix-B

Anova: Two-Factor With Replication

SUMMARY	**None:1**	**Low:2**	**Medium:3**	**High:4**	**Total**
low:1					
Count	3	3	3	3	12
Sum	19.8	22	26.2	29.9	97.9
Average	6.6	7.333333	8.733333	9.966667	8.158333
Variance	0.52	0.303333	0.253333	0.163333	2.055379
Medium:2					
Count	3	3	3	3	12
Sum	26.6	29	30.2	31.3	117.1
Average	8.866667	9.666667	10.06667	10.43333	9.758333
Variance	0.093333	0.653333	0.443333	0.303333	0.640833
High:3					
Count	3	3	3	3	12
Sum	29.9	29.8	31.7	33.2	124.6
Average	9.966667	9.933333	10.56667	11.06667	10.38333
Variance	0.043333	0.203333	0.343333	0.123333	0.368788
Total					
Count	9	9	9	9	
Sum	76.3	80.8	88.1	94.4	
Average	8.477778	8.977778	9.788889	10.48889	
Variance	2.374444	1.824444	0.933611	0.376111	

ANOVA

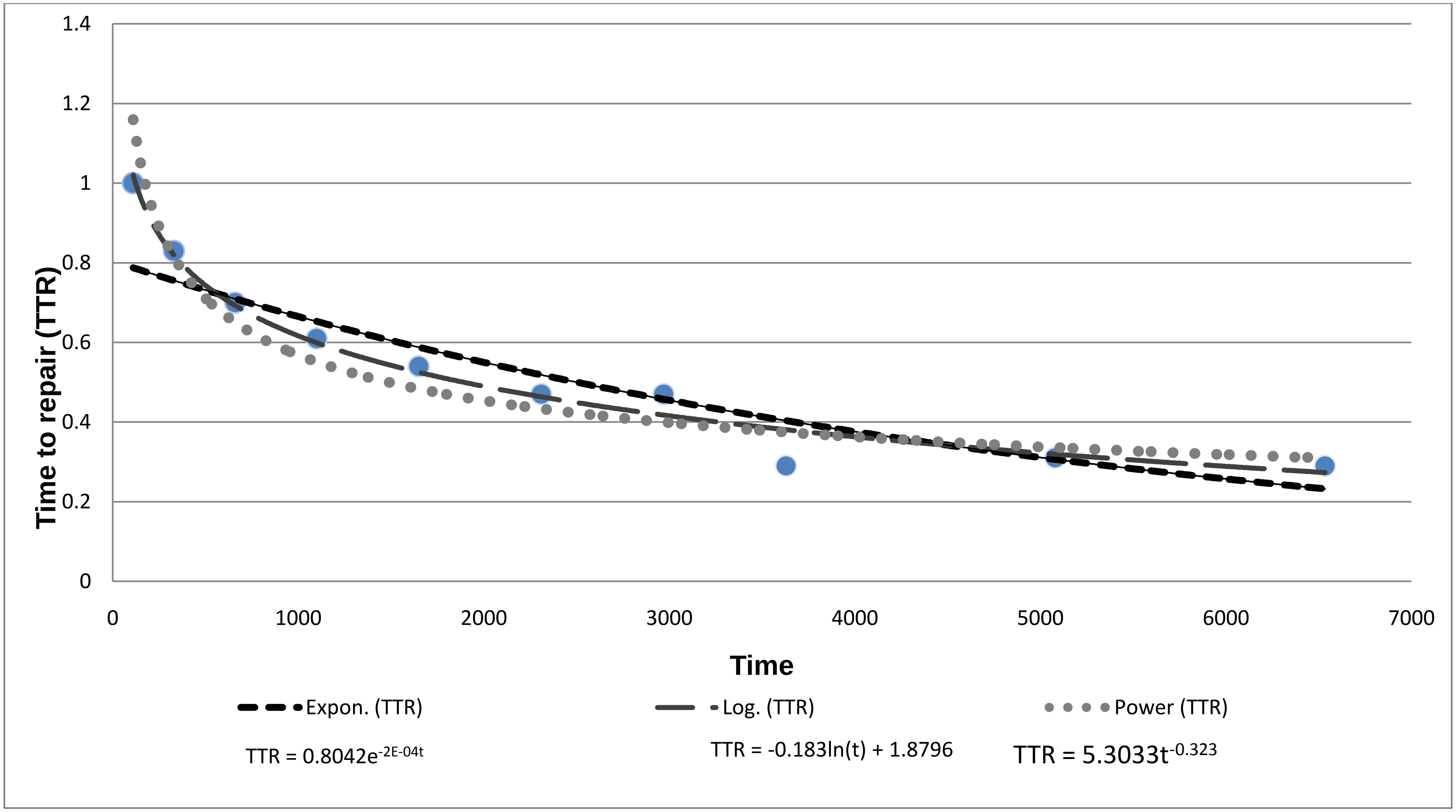
Source of Variation	SS	df	MS	F	P-value	F crit
Sample	31.605	2	15.8025	55.01838	1.09E-09	3.402826
Columns	21.25111	3	7.083704	24.6628	1.65E-07	3.008787
Interaction	5.570556	6	0.928426	3.232431	0.017973	2.508189
Within	6.893333	24	0.287222			
Total	65.32	35				

Appendix-C

0.7 < β < 1.27 (for high complex task) sample 1

n	$\widehat{TTR}$	*T*	*B*	*alpha*	*B-1*	*Part I*	*New model* $\widehat{TTR}$	*(TTR-* $\widehat{TTR}$ *)^2*
1	1	110	0.90	1000.00	-0.10	0.001	0.978435	0.000465
2	0.83	330	0.90	1000.00	-0.10	0.001	0.695458	0.018101
3	0.7	660	0.90	1000.00	-0.10	0.001	0.471512	0.052206
4	0.61	1100	0.90	1000.00	-0.10	0.001	0.299855	0.096190
5	0.54	1650	0.90	1000.00	-0.10	0.001	0.178201	0.130898
6	0.47	2310	0.90	1000.00	-0.10	0.001	0.098909	0.137708
7	0.47	2970	0.90	1000.00	-0.10	0.001	0.056253	0.171186
8	0.29	3630	0.90	1000.00	0.25	0.014	0.056	0.054756
9	0.31	5080	0.90	1000.00	-0.10	0.001	0.056	0.064516
10	0.29	6535	0.90	1000.00	-0.10	0.001	0.056	0.054756
							SSE	**0.780785**

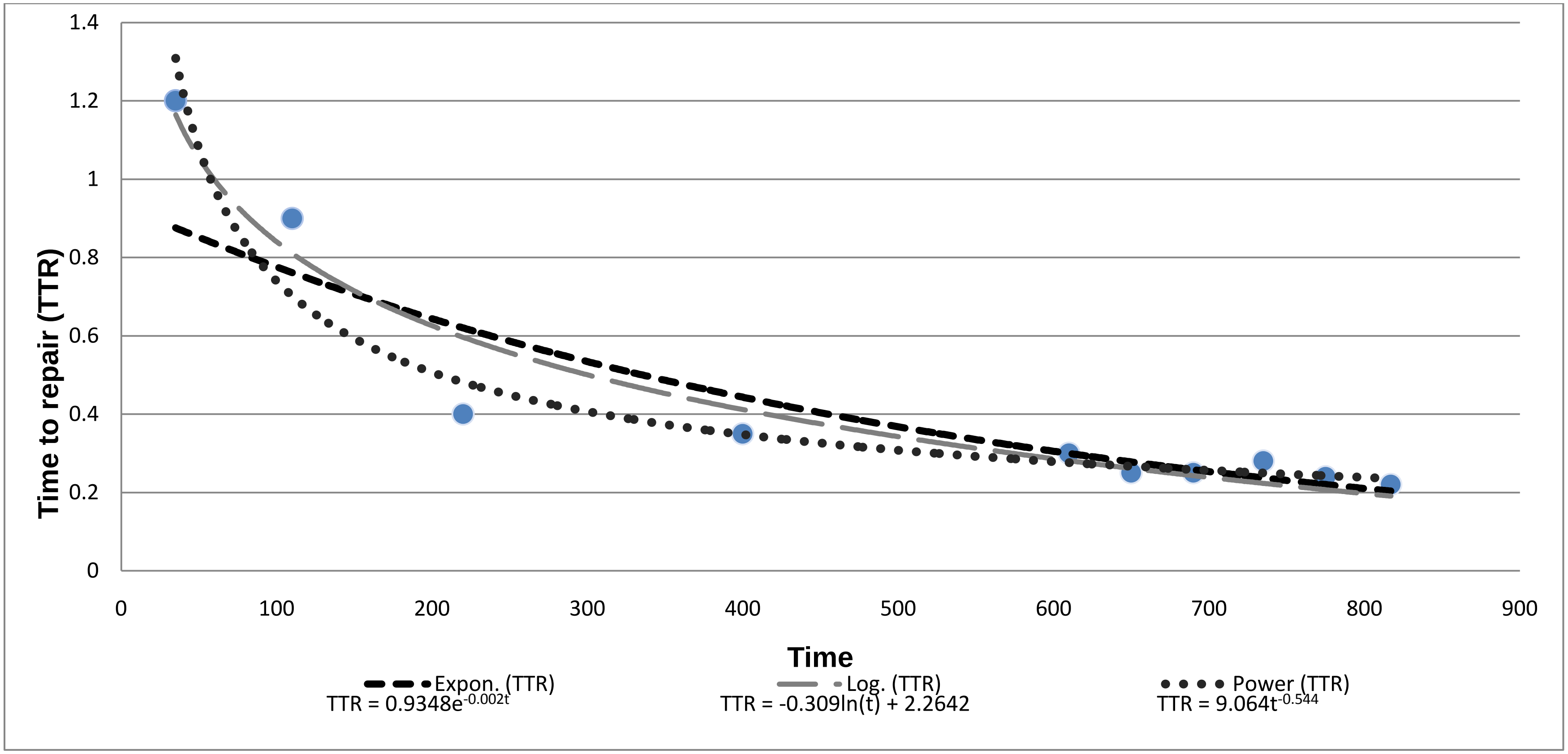
0.7 < β < 1.27 (for high complex task) sample 1



0.5 < β < 0.9 (for Medium complex task) sample 2

n	$\widehat{TTR}$	*T*	*B*	*alpha*	*B-1*	*Part I*	*New model* $\widehat{TTR}$	*(TTR-* $\widehat{TTR}$ *)^2*
1	1.2	35	**0.70**	1000.	-0.30	0.001	1.0966	0.0106913
2	0.9	110	**0.70**	1000	-0.30	0.001	0.6161	0.0805796
3	0.4	220	**0.70**	1000	-0.30	0.001	0.3754	0.0006028
4	0.35	400	**0.70**	1000	-0.30	0.001	0.2335	0.0135552
5	0.3	610	**0.70**	1000	-0.30	0.001	0.1456	0.0238327
6	0.25	650	**0.70**	1000	-0.30	0.001	0.23	0.0004
7	0.25	690	**0.70**	1000	-0.30	0.001	0.23	0.0004
8	0.28	735	**0.70**	1000	0.25	0.043	0.23	0.0025
9	0.24	775	**0.70**	1000	-0.30	0.000	0.23	1E-04
10	0.22	817	**0.70**	1000	-0.30	0.000	0.23	0.0001
							SSE	**0.132761932**

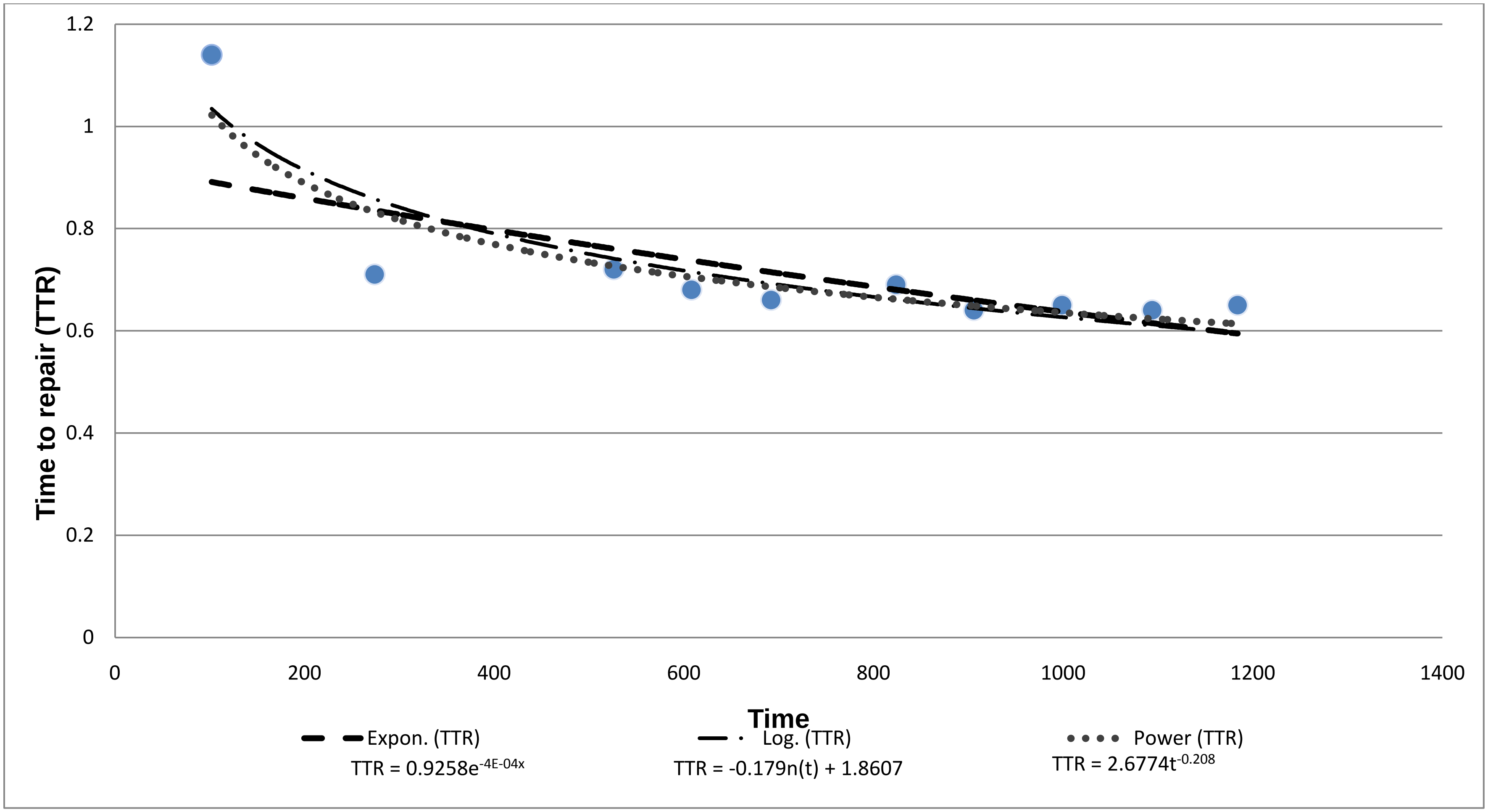
0.5 < β < 0.9 (for Medium complex task) sample 2



0.5 < β (for Low complex task) sample 3

n	$\widehat{TTR}$	*T*	*B*	*alpha*	*B-1*	*Part I*	*New model* $\widehat{TTR}$	*(TTR-* $\widehat{TTR}$ *)^2*
1	1.14	102	0.50	1000.00	-0.50	0.002	1.082018	0.003361915
2	0.71	274	0.50	1000.00	-0.50	0.001	0.490038	0.048383237
3	0.72	526	0.50	1000.00	-0.50	0.001	0.49	0.0529
4	0.68	608	0.50	1000.00	-0.50	0.000	0.49	0.0361
5	0.66	692	0.50	1000.00	-0.50	0.000	0.49	0.0289
6	0.69	824	0.50	1000.00	-0.50	0.000	0.49	0.04
7	0.64	906	0.50	1000.00	-0.50	0.000	0.49	0.0225
8	0.65	999	0.50	1000.00	0.25	0.123	0.49	0.0256
9	0.64	1094	0.50	1000.00	-0.50	0.000	0.49	0.0225
10	0.65	1184	0.50	1000.00	-0.50	0.000	0.49	0.0256
							SSE	**0.305845152**

0.5 < β (for low complex task) sample 3



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