Developing a Neural Network Model to Monitor and Predict Waiting Times in the Emergency Department

By

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A thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD) in Health Informatics

Deakin University

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Abstract

While quality management has been studied and practiced over several decades, has increased in more emphasis on using process management perspectives toward quality on more recent years and decades. In such perspective, quality control and management processes are designed to interact with other organisational processes in order to enable organisations to achieve their core strategies and goals.

In parallel with manufacturing context, quality management approaches toward provided services in service organisations have been growing as well. In particular, there have been different models for and discussions on service quality. Overall, service quality might be considered as the extent that provided services fulfill the expectations of customers. Moreover, managers in the service industry need to understand the types of service quality factors for their own service(s) and understand their various relationships between perception and performance in order to design, measure and control their service.

Taking the aforementioned discussions on quality management and service quality into the healthcare context, I review service quality models and their applications in the healthcare industry. That results in identification of some research gaps. For instance, often models of healthcare service quality face challenges in measuring quality. In addition, most models include qualitative and subjective measures, despite the fact that often there are influential quantitative factors that should be included in service quality models. Furthermore, for those models, one requires substantial amounts of data to
ensure that the generating results are reliable and useful. Lastly, and in particular, there have been few studies on application of the neural network models in the service industries.

Overall, I found the following research objectives highly motivating: (i) designing and developing of a neural networks model and its application in service quality control by using a comprehensive attribute and variable quality attributes, and (ii) applying neural networks as a dynamic model for forecasting service quality in order to make some proactive decisions rather than reactive ones.

In order to evaluate the application of a designed quality control model, I studied and analyzed a healthcare case study. This case study focuses on Length of Stay (LoS) at an emergency department, which is a critical part of the healthcare system. In particular, we collected data records (that include twenty-four independent variables) for 27,253 patients who visited emergency department in Melbourne in 2013.

Since the number of influential variables for LoS at ED are high, I designed a meta-algorithm in which an ANN model is embedded. The algorithm is iterative and depending on the desired performance measure (e.g. avoid over- or under-prediction) and features of ANN (e.g., transformation function, number of layers), it will iterate over a large number of scenarios, and then reports a number of scenarios (i.e., or models). In my results, I found that ANN models with the following features are likely to have high performance measures (e.g., low positive and negative, MSE errors): X1 (Age), X2 (Gender), X3 (Week day of Arrival), X4 (Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category).
In sum, the developed meta-algorithm and ANN models in this thesis can facilitate ED managers in coping with high uncertainty and complexity of diverse patients demands and limited available resources. In addition, it can be implemented in IT-platforms and get integrated with other healthcare-related information systems.
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Chapter 1
Introduction
CHAPTER 1: INTRODUCTION

1. Introduction

This chapter serves to set the scene for this research project. In particular, in order to provide an overall image of quality control systems in organizations, it discusses quality control systems and processes, and their constituent parts.

There are several definitions for “Quality” proposed by the most influential quality scholars such as Shewhart, Deming, Juran, Crosby, Feigenbaum, Taguchi, Garvin, and Ishikawa depending on their different points of view in their era. Competitive pressures and technological developments have affected the core knowledge of service industry and introduced many new concepts in the literature. The newest definition of quality is the “degree to which a set of inherent characteristics fulfils requirements” (ISO 2005). In this definition, a set of characteristics are defined as requirements in which defined as “need or expectation that is stated, generally implied or obligatory” (ISO 2005). It means that, for achieving an acceptable level of quality, all needs and expectations should be considered.

During the quality development from “operator quality control” to “quality management”, “process approach” was taken into consideration as a revolution in quality management concept in 2000 in the figure of ISO 9001:2000 standard and has been being continued in the newest version issued in 2015.
In this International Standard all organizations are encouraged to adopt a process approach when developing, implementing and improving the effectiveness of a quality management system, to enhance customer satisfaction by meeting customer requirements (Anand Prakash and Mohanty 2012). Such a process approach involves the systematic definition and management of processes, and their interactions, so as to achieve the intended results in accordance with the quality policy and strategic direction of the organization (Anand Prakash and Mohanty 2012).

The application of the process approach in a quality management system enables:

- Understanding and consistency in meeting requirements;
- The consideration of processes in terms of added value;
- The achievement of effective process performance;
- Improvement of processes based on evaluation of data and information (Anand Prakash and Mohanty 2012)

Figure 1 gives a schematic representation of any process and shows the interaction of its elements. The monitoring and measuring check points, which are necessary for control, are specific to each process and will vary depending on the related risks (Anand Prakash and Mohanty 2012).
In this approach, “quality control” needs to be considered as one of organization’s processes in product realization section in interaction with other processes. As is shown in this figure, the starting point is requirements stated by customer and the finish point is fulfilling the requirements. In service industry, the requirements that are stated or implied as input, are customer needs and expectations that should be measured as output, to make sure that all are fulfilled.

“Product” in this figure is analogous to service. Service is the result of at least one activity necessarily performed at the interface between the company and customer and is generally intangible (ISO 2005).

Provision of a service can involve, for example, the following:
-an activity performed on a customer-supplied tangible product (e.g. automobile to be repaired);

-an activity performed on a customer-supplied intangible product (e.g. the income statement needed to prepare a tax return);

-the delivery of an intangible product (e.g. the delivery of information in the context of knowledge transmission);

-the creation of ambience for the customer (e.g. in hotels and restaurants)(ISO 2005)

The PDCA (Plan=Do-Check-Act) cycle can be applied to all processes and to the quality management system as a whole. Figure 2 illustrates how Clauses 4 to 10 can be grouped in relation to the PDCA cycle. (Anand Prakash and Mohanty 2012)
Figure 2 — Representation of the structure of this International Standard in the PDCA cycle adopted from (Anand Prakash and Mohanty 2012)

Quality Control, defined as” part of quality management focused on fulfilling quality requirements”, is considered as one of the elements of quality management quality policy, quality objectives, quality planning, quality assurance and quality improvement(ISO 9000, 2015).

Juran introduces “Quality Control” as a part of his trilogy besides “quality planning” and “quality improvement”. The term “control of quality” emerged early in the twentieth century (Juran J.M. and Godfrey A.B. 1999).
In the United States, the term “quality control” now often has the narrow meaning defined previously. The term “total quality management” (TQM) is now used as the all-embracing term. In Europe, the term “quality control” is also acquiring a narrower meaning. Recently, the European umbrella quality organization changed its name from European Organization for Quality Control to European Organization for Quality. In Japan, the term “quality control” retains a broad meaning. Their “total quality control” is roughly equivalent to U.S. term “total quality management.” In 1997, the Union of Japanese Scientists and Engineers (JUSE) adopted the term total quality management (TQM) to replace total quality control (TQC) to more closely align themselves with the more common terminology used in the rest of the world (Juran J.M. and Godfrey A.B. 1999).

The quality control process is one of the steps in the overall quality planning sequence. Figure 3 shows the input-output features of this step. In Figure 3, the input is operating process features developed to produce the service features required to meet customer needs. The output consists of a system of service and process controls which can provide stability to the servicing process (Juran J.M. and Godfrey A.B. 1999).
Figure 3 — the input-output diagram for the quality control process (Juran J.M. and Godfrey A.B. 1999)

Unlike goods quality, which can be measured objectively by such indicators as durability and number of defects (Crosby Philip B. 1979; Garvin David A. 1983), service quality is an abstract and elusive construct because of three features unique to services: intangibility, heterogeneity, and inseparability of production and consumption (Parasuraman A., Valarie A. Zeithaml et al. 1985). In the absence of objective measures, such subjective methods as SERVQUAL (Parasuraman A., Valarie A. Zeithaml et al. 1988), SERVPERF(Cronin J. J. and Taylor S. A. 1992), Qualitometro (Franceschini F., Cignetti M. et al. 1988) have been developed since 1991.

Artificial neural networks are, as their name indicates, computational networks which attempt to simulate, in a gross manner, the networks of nerve cell (neurons) of the biological (human or animal) central nervous system (Daniel Graupe 2007). Amid meta-heuristic algorithms including artificial neural networks, Genetic Algorithm, Tabu search, Ants Clone and simulated annealing, The first one is the most famous and applicable one due to its vast range of applications in different science domain including quality control( Abbasi Babak 2007). In recent years, some researches have been done in this area, but all have been limited in manufacturing domain and goods quality control.

In summary, according to the discussions in this chapter, the newest definition of quality is the “degree to which a set of inherent characteristics fulfils requirements” (ISO 2005).
Moreover, as stated by the International quality Standard, all organizations are encouraged to adopt a process approach for their quality management systems. In this perspective, quality control process should interact with other organizational processes.

In this research, I am going to review the major proposed subjective and objective methods for controlling service quality and to study the artificial neural network methodology and its application in this area.

In this thesis, chapter 2 discusses the existing literature concerning Service quality, Service quality models, Service Quality in Healthcare and Neural networks. In chapter 3, the research model and hypothesis are explained. This chapter includes the knowledge gap and problem statement, research objectives and research questions.

Chapter 4 includes the research model and hypothesis for Artificial Neural Network. In order to carry out simulation studies on the performance of the proposed method, it is necessary to apply a data generation method, section 4.2 of chapter 4 discusses the case study or application of ANN in emergency department of a private hospital.

Chapter 5 includes the results of the case study which has been discussed in chapter 6. Section 6 also includes a conclusion of the research and the findings as well as opportunities that can be considered as future work for other researchers. As an outcome of this research study, one paper and one book chapter have been already published in the international journals and are available in appendix B and C. The researcher of this thesis has been holding a PhD degree since 2014 and the PhD thesis submitted in 2014 is available in Appendix D.
Chapter 2
Literature Review
CHAPTER 2 – LITERATURE REVIEW

2. Literature Review

In this chapter, an overview of the relevant literatures to the topic of this thesis is provided. The relevant streams of the literature include research papers about service quality, service quality models, service quality in healthcare, and finally neural networks.

2.1 Service Quality

In today’s world and in this competitive market, service-delivering companies attempt to achieve a specific and distinguished position over other competitors through getting unique advantaged to fulfill their customer needs and expectations and consequently to achieve customer satisfaction. On the other hand, customer and consumers also are always in seek of suppliers that offer much better quality services and meet their expectations. (Mahdavinia H. 2007)

The concept of service quality as a whole construct is large and varied. The theory has been elaborated on by many researches. The conceptual foundation for service quality was emerged from the works of a handful of researchers who have examined the meaning of service quality (Sasser W. W., Olsen R. P. et al. 1978; Gronroos Christian 1982).
Parasuraman et al. (Parasuraman A., Valarie A. Zeithaml et al. 1985) write service quality as the difference between customer expectation and perception.

Service quality is usually expressed from customer point of view as a function of customer’s expectations of the service to be provided compared to their perception of the actual service experience (Gronroos Christian 1984; Parasuraman A., Valarie A. Zeithaml et al. 1985; Johnston R. and Heineke J. 1998). It was showed that using service quality as a key point of marker differentiation positively influence customer retention and market growth (Imrie B. C., Cadogan J. W. et al. 2002). However, (Parasuraman A., Valarie A. Zeithaml et al. 1988) stated that in measuring perceived service quality, the level of comparison is what a customer should expect, whereas, in measures of customer satisfaction, the appropriate comparison is what a customer would expect (Mahdavinia H. 2007; Daniela Carlucci, Paolo Renna et al. 2013; Das 2014), says the quality of the service can be defined as a measure of the extent to which the provided service corresponds to the expectations of the clients. Therefore, the quality perceived in the provision of a service became a determinant success factor in every field of a commercial activity (Connolly 2007; Lee 2014).

Some other researchers have focused on role of employee in service quality and consequently customer satisfaction. (Hartline M., III J. M. et al. 2002) stated that in many cases, customer contact employees are the first and only representatives of a service firm. Therefore, customer often base their impressions of the firm largely on the service received from customer contact employees. (Mahdavinia H. 2007).
In management perspective, it is suggested that managers need to understand the types of
service quality factors for their own service(s) and understand their various relationships
between perception and performance in order to design, measure and control their
service. Service levels need to be set and strategies devised, that first recognize the
relative impact of individual factors on overall perceptions and secondly, link them to

2.2 Service Quality Models

There have been five predominant measurement tools since 1991. These tools all differ in
theoretical background, data collection, sample size dimensions and response. The
following are the five measurement tools:

Two-way

Two-way used latent evaluations factors based on the theory that service quality is
evaluated by answers given by customers about “objective” (quality attribute) and
“subjective” (satisfaction level). The survey was sent to 330 service including banks,
restaurants, laundries and supermarket. Schvaneveldt employed a five-point semantic
scale, to examine the five dimensions. Performance, security completeness, ease of use
and emotively/environment (Schvaneveldt S. and Enkawa T. 1991) (Mahdavinia H.
2007).
**SERVPERF**

Cronin and Taylor (Cronin J. J. and Taylor S. A. 1992) proposed SERVPREF based on their survey on theory that service quality is evaluated by perception only and used two banks, pest control companies, laundries and fast food companies with a sample size of 600. They also used a seven-point semantic differential scale and utilized the same dimensions as the SERVQUAL study. The key difference was that only perceptions were evaluated (Mahdavinia H. 2007). SERVQUAL will be explained in details next page onwards,

**Normed quality**

Normed quality (Teas R. K. 1994) was based on the theory that the problem for expectation runs to a redefinition of this component and discriminate between ideal expectation and feasible expectation to calculate service quality and was conducted on three large department stores with a sample size of 120. It also employed the same semantic scale and dimensions as SERVQUAL.

That model is the second well-known model after SERVREF that is derived from SERVQUAL. In this model, instead of considering the discrimination between customer’s expectation and perception, the discrepancy between customer ideal expectation and feasible expectation is reckoned. (Ghoseiri K. and Pishdad S. 2006).
Normed Quality model includes five 10-question parts in the figure of SERVQUAL 5-dimension by applying the seven-point semantic differential scale (Thongsamak Sasima 2001).

**Qualitometro**

Qualitometro (Franceschini F., Cignetti M. et al. 1988) is founded on the determinants of service quality. Customer expectations and perceptions are evaluated in two distinct moments. Quality evaluation is carried out by means of a comparison between quality and expectations and perception profile. The study was conducted in library facility, utilizing a sample size of 100.

It also deployed the same semantic scale and dimensions as SERVQUAL (Mahdavinia H. 2007).

**SERVQUAL**

All above-mentioned models that, were proposed after the first introduction of SERVQUAL in 1988 by Parasuraman et al (Parasuraman A., Valarie A. Zeithaml et al. 1988), have applied this model as a base.

SERVQUAL is used to measure consumer’s and service providers’ expectations and perceptions. This approach enables the exceptions and perceptions gaps to be assessed,
while providing a measure of the service quality gap and the service delivery gap. According to Parasuraman et al’s., (1988) model, the gap between consumer’s expectations and perceptions are a function of several other gaps in the service delivery process (Mangold G. and Emin B. 1991).

The original survey was based on two telephone companies, Insurance companies and banks with a sample size ranging from 290- 497. Parasuraman et al. (Parasuraman A., Leonard L Berry et al. 1991) utilized a seven-point semantic differential scale. The survey consisted of the following five dimensions: tangibles, reliability, assurance, responsiveness, and empathy. To evaluate these five aspects of service quality, they designed a questionnaire including 22 pairs of questions, half of these questions related to customer’s expectations and the other half are related to customer’s perceptions of services (Mahdavinia H. 2007).

Apart from aforementioned categorization, Seth and Deshmukh (Nitin Seth and S.G. Deshmukh 2005) reviewed the current models from another angle. Some of them are designed for specific industries “Internet banking model”, IT-based model, and etc. All 19 service quality models have been entitled as below:

**SQ1. Technical and functional quality model (Gronroos Christian 1984)**

The author identified three components of service quality, namely: “technical quality” as the quality of what consumer actually receives; “functional quality” as how the customer gets the technical outcome; and “image” that can be expected to build up mainly by
"technical and functional quality of service including the other factors (tradition, ideology, word of mouth, pricing and public relations).

SQ2: GAP model (SERVQUAL) (Parasuraman A., Valarie A. Zeithaml et al. 1985)

They proposed that service quality is a function of the differences between expectation and performance along the quality dimensions. They developed a service quality model based on gap analysis. The five gaps visualized in the model are “Difference between consumers’ expectation and management’s perceptions of those expectations”, “Difference between management’s perceptions of consumer’s expectations and service quality specifications”, “Difference between service quality specifications and service actually delivered”, “Difference between service delivery and the communications to consumers about service delivery”, “Difference between consumer’s expectation and perceived service”

According to this model, the service quality is a function of perception and expectations. This exploratory research was refined with their subsequent scale named SERVQUAL (Parasuraman A., Valarie A. Zeithaml et al. 1988). At this point the original ten dimensions of service quality collapsed in to five dimensions: reliability, responsiveness, tangibles, assurance (communication, competence, credibility, courtesy, and security) and empathy which capture access and understanding/knowing the customers. Later SERVQUAL was revised in 1991 by replacing “should” word by “would” and in 1994 by reducing the total number of items to 21, but five-dimensional structure remaining the same. In addition to this empirical research, the authors characterized and further
delineated the four gaps identified in their research of 1985 for measuring customers’ perceptions of service quality.

**SQ3. Attribute service quality model (Haywood-Farmer J. 1988)**

This model states that a service organization has “high quality” if it meets customer preferences and expectations consistently. According to this, the separation of attributes into various groups is the first step towards the development of a service quality model. In general, services have three basic attributes: physical facilities and processes; people’s behavior; and professional judgment. Each attribute consists of several factors.


A service quality gap may exist even when a customer has not yet experienced the service but learned through word of mouth, advertising or through other media communications. Thus, there is a need to incorporate potential customers’ perceptions of service quality offered as well as actual customers’ perceptions of service quality experienced. The synthesised model of service quality considers three factors, viz. company image, external influences and traditional marketing activities as the factors influencing technical and functional quality expectations.

**SQ5. Performance only model (SERVPERF) (Cronin J. J. and Taylor S. A. 1992)**

They argued on the framework of (Parasuraman A., Valarie A. Zeithaml et al. 1985), with respect to conceptualization and measurement of service quality and developed
performance only measurement of service quality called SERVPERF by illustrating that service quality is a form of consumer attitude and the performance only measure of service quality is an enhanced means of measuring service quality. They argued that SERVQUAL confounds satisfaction and attitude. They stated that service quality can be conceptualized as “similar to an attitude” and can be operationalized by the adequacy-importance model. In particular, they maintained that Performance instead of “Performance-Expectation” determines service quality.

SQ6. Ideal value model of service quality (Mattsson J. 1992)

The model argues for value approach to service quality, modeling it as an outcome of satisfaction process. This value-based model of service quality suggests the use of a perceived ideal standard against which the experience is compared. Implicit negative disconfirmation on a pre-conscious value level, is then hypothesized to determine satisfaction on a “higher” attitude level. This negative disconfirmation is the major determinant of consumer satisfaction, more attention should be given to cognitive processes by which consumers’ service concepts are formed and changed.


According to the author the conventional disconfirmation model has conceptual, theoretical and measurement problems. He pointed out that following issues in the measurement of service quality, i.e. SERVQUAL (Parasuraman A., Valarie A. Zeithaml et al. 1988) as: conceptual definition ambiguity; theoretical justification of expectations in the measurement of service quality; the usefulness of the probability
specification in the evaluated performance (EP) measurement; and link between service quality and consumer satisfaction/dissatisfaction. The author proposed Evaluated performance (EP) framework and Normed quality model: as two frameworks for service quality.

SQ8. IT alignment model (Berkley B.J. and Gupta A. 1994)

This model describes in detail where IT had been used or could be used to improve specific service quality dimensions including reliability, responsiveness, competence, access, communications, security, understanding and knowing the customers. Through some case studies use of IT for quality control (collect customer data, monitor operations and facilitate service) is also demonstrated. According to the model, it is important that service quality and information system (IS) strategies must be tightly coordinated and aligned. The model explains the process of aligning service and aligning strategies.

SQ9. Attribute and overall affect model (Dabholkar P.A. 1996)

The attribute model is based on what consumers would expect from such option. It is based on cognitive approach to decision making, where consumers would use a compensatory process to evaluate attributes associated with the technology based self-service option in order to form expectations of service quality.

The overall affect model (Figure 8(b)) is based on the consumers’ feeling towards the use of technology. It is based on an effective approach to decision making where consumers would use overall predispositions to form expectation self-service quality for a technology-based self-service option.
In both the models expected service quality would influence intentions to use technology-based self-service option.


This model attempts to enhance the understanding of the constructs perceived service quality and consumer satisfaction. The model highlights the effect of expectations, perceived performance desires, desired congruency and expectation disconfirmation on overall service quality and customer satisfaction. These are measured through set of ten attributes of advising.

SQ11. PCP attribute model (Philip G. and Hazlett S.A. 1997)

The authors propose a model that takes the form of a hierarchical structure – based on three main classes of attributes – pivotal, core and peripheral. When a consumer makes an evaluation of any service encounter, he is satisfied if the pivotal attributes are achieved, but as the service is used more frequently the core and peripheral attributes may began to gain importance.

SQ12. Retail service quality and perceived value model (Sweeney J.C., Soutar G.N. et al. 1997)
The influence of service quality on value and willingness to buy in a specific service encounters through two alternative models. Value construct used in this model is “value for money”.

- **Model 1:** this model highlights that in addition to product quality and price perceptions, functional service quality and technical service quality perceptions both directly influence value perceptions.

- **Model 2:** this model highlights that in addition functional service quality perceptions directly influence consumers’ willingness to buy. Functional service quality perceptions also influence technical service quality perceptions, which in turn influence product quality perceptions and neither of the two directly influence value perceptions.

**SQ13. Service quality, customer value and customer satisfaction model (Oh H. 1999)**

The proposed model focuses mainly on post purchase decision process. The model incorporates key variables such as perceptions, service quality, consumer satisfaction, customer value and intentions to repurchase. The model provides evidence that customer value has a significant role in customer’s post-purchase decision-making process. It is an immediate antecedent to customer satisfaction and repurchase intentions. Results also indicate that perceived price has a negative influence on perceived customer value and no relationship with perceived service quality.

A comprehensive model of service quality includes an examination of its antecedents, consequences, and mediators to provide a deeper understanding of conceptual issues related to service quality. This model examines some conceptual issues in service quality as: the relevant factors related to service quality better conceived as components or antecedents and the relationship of customer satisfaction with behavioral intentions.

SQ15. Internal service quality model (Frost F.A. and Kumar M. 2000)

The authors have developed an internal service quality model based on the concept of GAP model (Parasuraman A., Valarie A. Zeithaml et al. 1985). The model evaluated the dimensions, and their relationships, that determine service quality among internal customers (front-line staff) and internal suppliers (support staff) within a large service organization.

SQ16. Internal service quality DEA model (Soteriou A.C. and Stavrinides Y. 2000)

The authors presented a service quality model that can be used to provide directions to a bank branch for optimal utilization of its resources. The model does not aim to develop the service quality measures, rather guides how such measures can be incorporated for service quality improvements. The model points out resources that are not properly utilized. The data envelope analysis (DEA) model compares branches on how well they transform the resources (inputs) to achieve their level of service quality (output) given the client base. The DEA model will identify under-performers and suggest ways for their improvement.

SQ16. Benchmarking of service quality with DEA (Lee 2014)
It proposes a data envelopment analysis (DEA) approach to measurement and benchmarking of service quality. Dealing with measurement of overall service quality of multiple units with SERVPERF as multiple-criteria decision-making (MCDM), the proposed approach utilizes DEA, in particular, the pure output model without inputs. The five dimensions of SERVPERF are considered as outputs of the DEA model. A case study of auto repair services is provided for the purpose of illustration. The current practice of benchmarking of service quality with SERVQUAL/SERVPERF is limited in that there is little guidance to whom to benchmark and to what degree service quality should be improved. It contributes to the field of service quality benchmarking by overcoming the above limitations, taking advantage of DEA’s capability to handle MCDM problems and provide benchmarking guidelines.

SQ17. Internet banking model (Broderick A.J. and Vachirapornpuk S. 2002)

This study proposes and tests a service quality model of internet banking (Figure 16). The research uses participant observation and narrative analysis of UK internet web site community to explore how internet banking customers perceive and elements of this model. In the context of internet, five key elements are treated as central influences on perceived service quality: They are: customer expectations of the service; the image and reputation of the service organization; aspects of the service setting; the actual service encounter; and customer participation.

It proposes a service quality model that links customer perceived IT-based service options to traditional service dimensions.

The model attempts to investigate the relationship between IT-based services and customers’ perceptions of service quality. The IT-based service construct is linked to service quality as measured by SERVQUAL (Parasuraman A., Valarie A. Zeithaml et al. 1988; Parasuraman A., Leonard L Berry et al. 1991).

The model focuses on the linkages among the service dimensions as measured by SERVQUAL, the constructs representing the IT-based service quality, preferences towards traditional services, experiences in using IT-based services, and perceived IT policies. The impacts of these constructs on perceived service quality and customer satisfaction are also specified.

**SQ19. Model of e-service quality (Santos J. 2003)**

This study proposes a conceptual model of e-service quality with its determinants. It is proposed that e-service quality have incubative (proper design of a web site, how technology is used to provide consumers with easy access, understanding and attractions of a web site) and active dimensions (good support, fast speed, and attentive maintenance that a web site can provide to its customers) for increasing hit rates, stickiness, and customer retention.

The SERVQUAL models and their findings /applications are summarised in table 1 below (Nitin Seth and S.G. Deshmukh 2005):
<table>
<thead>
<tr>
<th>Models</th>
<th>Summary of Key findings/applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>SQ1. Technical and functional quality</td>
<td>• Depends on technical quality, functional quality and corporate image of the organization</td>
</tr>
<tr>
<td>model</td>
<td>• Functional quality is more important than the technical quality</td>
</tr>
<tr>
<td>SQ2. Gap model</td>
<td>• An analytical tool.</td>
</tr>
<tr>
<td></td>
<td>• Identifies numbers of variables affecting the quality of the offering</td>
</tr>
<tr>
<td></td>
<td>• Externally focused model</td>
</tr>
<tr>
<td></td>
<td>• Identifies the relevant service quality factors from the viewpoint of the consumer</td>
</tr>
<tr>
<td>SQ3. Attribute service quality model</td>
<td>• Segregating service organization on three dimensions</td>
</tr>
<tr>
<td></td>
<td>• Help to guide about targeting towards the right customer segment</td>
</tr>
<tr>
<td>SQ4. Synthesized model of service quality</td>
<td>• Improve the success of service offerings in any industry</td>
</tr>
<tr>
<td></td>
<td>• Require systematic management attention in planning, implementation and controlling service-marketing strategies</td>
</tr>
<tr>
<td>SQ5. Performance only model</td>
<td>• Service quality should be conceptualized and measured as an attitude</td>
</tr>
<tr>
<td></td>
<td>• Service quality is an antecedent of consumer satisfaction</td>
</tr>
<tr>
<td>SQ6. Ideal value model of service quality</td>
<td>• Incorporates and defines the importance of diverse components of the service</td>
</tr>
<tr>
<td></td>
<td>• Highlights attention to the importance of negative disconfirmation experience</td>
</tr>
<tr>
<td>SQ7. EP and NQ model</td>
<td>• Raised a number of issues pertaining to conceptual and operational definitions of expectation and revised expectation</td>
</tr>
<tr>
<td></td>
<td>• The criterion and construct validity of the EP model was higher than both the SERVQUAL and NQ model.</td>
</tr>
<tr>
<td>SQ8. IT alignment model</td>
<td>• Describe how IT can be used to improve customer service</td>
</tr>
<tr>
<td></td>
<td>• Realize the complete benefit of using information systems</td>
</tr>
<tr>
<td>SQ9. Attribute and overall affect model</td>
<td>• It is favored in forming the evaluations of service quality for technology-based self-service options</td>
</tr>
<tr>
<td></td>
<td>• It does not add further explanatory power to the attribute-based model</td>
</tr>
<tr>
<td>SQ10. Model of perceived quality and</td>
<td>• It shows that service quality and satisfaction are distinct and desires congruency does influence satisfaction.</td>
</tr>
<tr>
<td>satisfaction</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ11. PCP attribute model</td>
<td>• Simple, effective and general framework of assessing service quality for any service sector</td>
</tr>
<tr>
<td></td>
<td>• Highlights the area of improvements for service quality depending on the frequency of encounter</td>
</tr>
<tr>
<td>SQ12. Retail service quality and</td>
<td>• The technical service quality is an important contributor to product quality and value perceptions and hence influences willingness to buy</td>
</tr>
<tr>
<td>perceived value</td>
<td>• Functional service quality has indirect influence on willingness to buy</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ13. Service quality, customer value and</td>
<td>• Framework for understanding consumer decision process as well as evaluating company performance</td>
</tr>
<tr>
<td>customer</td>
<td>• Provides directions and targets for customer-oriented company efforts</td>
</tr>
</tbody>
</table>
Table 1 — Summary of SERVQUAL Models

<table>
<thead>
<tr>
<th>Model Description</th>
<th>Key Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>satisfaction model</td>
<td></td>
</tr>
<tr>
<td>SQ14. Antecedents and mediator model</td>
<td>• Provide complete understanding of service quality and how these evaluations are formed</td>
</tr>
<tr>
<td></td>
<td>• Customer satisfaction is a better predictor of behavioral intentions</td>
</tr>
<tr>
<td>SQ15. Internal service quality model</td>
<td>• Consider the perceptions and expectations of internal customers and internal suppliers in recognizing the level of internal service quality perceived</td>
</tr>
<tr>
<td>SQ16. Internal service quality DEA model</td>
<td>• Indicates the resources, which can be better utilized to produce higher service quality levels</td>
</tr>
<tr>
<td>SQ17. Internet banking model</td>
<td>• Implication for the management of quality in internet banking service</td>
</tr>
<tr>
<td></td>
<td>• The level and nature of customer participation had the greatest impact on the quality of service experience and issues</td>
</tr>
<tr>
<td>SQ18. IT-based model</td>
<td>• Direct impact on the reliability, responsiveness and assurance dimensions and indirect impact on customer satisfaction and perceived service quality IT</td>
</tr>
<tr>
<td></td>
<td>• The customer evaluation of IT-based services is affected by preference towards traditional services, past experience in IT-based services and perceived IT policies</td>
</tr>
<tr>
<td>SQ19. Model of e-service quality</td>
<td>• Provides a better understanding of e-service quality</td>
</tr>
<tr>
<td></td>
<td>• It can be of assistance to all companies that engage e-commerce or plan to do so</td>
</tr>
</tbody>
</table>

Amid above-mentioned models, SERVQUAL may have some considerable merits that justify its application. Some of them are enlisted as below (Ghoseiri K. and Pishdad S. 2006):

a) Until a better but equally simple model emerges SERVQUAL will predominate as a service quality measure (Asubonteng P., McCleary K. J. et al. 1996)
b) Its high validity and reliability that are proved in many researches (Parasuraman A., Valarie A. Zeithaml et al. 1988; Kang H. and G. 2002)

c) Measuring customer expectation in SERVQUAL is another positive point of this model. Understanding consumers’ service quality expectations is the key to delivering service quality (Bebko C. P. 2000).

d) A particular advantage of SERVQUAL is that it is a tried and tested instrument which can be used comparatively for benchmarking purposes (Brysland A. and Curry A. 2001).


For detailed review and critique of SERVQUAL works of (Asubonteng P., McCleary K. J. et al. 1996; Buttle F. 1996) can be used as a reference(Nitin Seth and S.G. Deshmukh 2005).
2.3 Service Quality in Healthcare

The analysis for service quality in health care has been illustrated as below (Siripen Larpkiattaworn. 2003):

In the competitive circumstances, service sector is required to deliver continuing performance and quality improvement while being customer oriented.

In last few years, healthcare has transformed to one of the complicated trades in the world (Massimo Bertolini, M. Bevilacqua et al. 2011).

Measuring service quality in healthcare business is not simple to assess as understanding the patient perception and satisfaction is complicated and important (Panchapakesan Padma, Chandrasekharan Rajendran et al. 2010). The plausible reason may be that in healthcare industry, various medical centers and hospitals provide the similar kind of services, but they do not provide the same quality of services (Fayek Youssef, Deon Nel et al. 1995). Therefore, studying the service quality in healthcare is necessary. Additionally, clients today are more aware of options being offered and rising standards of services. These alterations have increased their anticipations (Puay Cheng Lim 2000).

With more competition because of broad and tough market conditions as well as the necessity to please patients, the components of quality control, quality service and effectiveness of medical treatment have become vital (Norazah Mohd Suki, Jennifer Chiam Chwee Lian et al. 2011) To conquer these matters, SERVQUAL scales have been used in healthcare studies to evaluate customers’ perception of service quality in a number of service classifications like patient satisfaction, acute care hospital, etc. (Puay

In a study done by (R Rohini and Mahadevappa 2006), SERVQUAL framework and elements are applied in their study on Bangalore (India) hospitals. They gained the opinions of both the patients and the hospital management. The study determined that there exist a total gap between patient’s perceptions and expectations and also between management’s perception and expectations.

The writers provided suggestions to fill those gaps. (M. Sadiq Sohail 2003) measured the service quality in Malaysia using the SERVQUAL model and found that all scores for perception exceeded the expectations for all factors examined. This illustrated that the perceived value of service quality has exceeded the initial anticipation for all variables within all dimensions. (Jayesh P. Aagja and Garg 2010) developed a scale for measuring perceived service quality for one public hospital from the user’s (patient’s) perspective. The goal was to measure perceived service quality of public hospitals. (Mayuri Duggirala, Chandrasekharan Rajendran et al. 2008) proposed that healthcare service quality contained of seven dimensions, namely, infrastructure, personnel quality, process of clinical care, administrative procedures, safety indicators, experience of medical care and social responsibility.
Strawderman (Strawderman 2005) researched on human factors. To model service quality, six dimensions were proposed whereby the five dimensions of SERVQUAL were used (i.e., responsiveness, trustworthiness, assurance, empathy and tangibles). A sixth dimension, usability, was added in a revised survey instrument named SERVUSE. Both measurement tools, SERVQUAL and SERVUSE, were found to be important predictors of service quality, satisfaction and behavioral intention in the healthcare setting.

In the other study by Eleuch (Eleuch 2011) evaluated Japanese patients’ healthcare service quality perceptions via a nonlinear approach. The study uses a nonlinear approach to assess patient total quality perceptions in order to improve knowledge. In a study undertaken by (Mohsin Muhammad Butt and Run 2010) developed and test validated the SERVQUAL model to measure the Malaysian private health service quality. Means, correlations, principal component and confirmatory factor analysis (CFA) were implemented to establish the modified SERVQUAL scale’s reliability, underlying dimensionality and convergent, discriminant validity.

Aaron et al (Aaron A. Abuosi and Atinga 2013) examined two key matters in healthcare centres, one to assess patients’ hospital service quality perceptions and expectation using SERVQUAL and other to outline the different concepts used to evaluate patient perceptions. In doing so, they observed that patient expectations were not being met during medical treatment. In spite of SERVQUAL’s popularity, some authors established their own instrument to A study by(Herman Akdaga, Turgay Kalaycıb et al. 2014) applied the fuzzy multiple criteria decision-making (MCDM) to evaluate the service quality of Istanbul (Turkey) hospitals. The authors make use of many MCDM techniques
to evaluate the hospitals service quality like AHP, TOPSIS, Yager’s min-max approach together with some numerical application techniques. The results were gained and compared.

In last few years, service quality and patient satisfaction has obtained increasing attention particularly in healthcare context (Mohammad Azam, Zillur Rahman et al. 2012), (Motasim Badri, Susan Cleary et al. 2006), (Anne S. York and McCarthy 2011). Moreover, previous studies depicted that there is a robust relationship between service quality and patient satisfaction (Masood A. Badri, Samaa Taher Attia et al. 2008) and (Kitapci, Akdogan et al. 2014). In the healthcare industries, service quality and patient satisfaction have been considered as two major matters. Significance of patient satisfaction particularly service encounters is well documented in the marketing and management literature (Gavriel Meirovich and Bahnan 2008).

Service quality in service encounters is frequently showed as being the result of a cooperating process between the service provider and the service receiver. The interactive features of service quality in service encounters are thus, crucial to the ultimate outcome (Nana Owusu-Frimpong, Sonny Nwankwo et al. 2010).

There are few studies which concentrate on service quality and patient satisfaction. Many of them illustrated realistic evidences for the positive link between service quality and patient satisfaction (Strawderman 2005); Padma (Panchapakesan Padma, Chandrasekharan Rajendran et al. 2010), (Sang M. Leea, DonHee Leea et al. 2012).
A inclusive structural equation-based service quality and patient satisfaction model was established and presented by Badri et al (Masood A. Badri, Samaa Taher Attia et al. 2008) to measure the patient’s situation before and after discharge in United Arab Emirates public hospitals. The structural equation modelling (SEM) supported the healthcare quality-patient status-satisfaction model.

Further, a study by some researchers (Nana Owusu-Frimpong, Sonny Nwankwo et al. 2010) assessed patients’ satisfaction with access to services in both public and private healthcare sectors in London. The outcome depicted various access experiences among public and private care clients.

In another study by York and McCarthy (Anne S. York and McCarthy 2011) on patient, staff and physician satisfaction, established a new model and instrument for measuring customer-satisfaction level and compared it with traditional techniques applying data gathering from healthcare medical centres. Findings revealed that the ultimate question provides same ratings to existing models at lower costs.

At last, (Kitapci, Akdogan et al. 2014) explored the effect of service quality dimensions on patient satisfaction, depicted the effect of satisfaction on word-of-mouth communication and repurchase intention and searched a important relationship between word-of-mouth and repurchase intention in Turkish healthcare trades. The study approved SERVQUAL variables and used SEM. They found that responsiveness and assurance dimensions are linked to CS.
2.4. Neural Networks

In this subsection, applications of neural networks in areas such as quality control and service analysis, are discussed.

2.4.1. Application in Quality Control

Neural networks have been applied to quality control and especially to statistical process control (SPC) since late 1980s. A principal reason for applying neural networks to SPC is to automate SPC chart interpretation (Pugh G. A. 1989). To date, the application of neural networks to quality control has been limited to SPC chart and has focused primarily on manufacturing. In the other words, no researches have been done in application of neural network in service quality. The literature review for its application to SPC in manufacturing has been briefly depicted as below (Siripen Larpkiattaworn. 2003):

Some researchers have focused on application of neural network to control the quality of one single measurable quality characteristic (univariate) which has been researched from different angles by: (Zorriassatine F. and Tannock J.D.T. 1998), (Pugh G. A. 1989), (Guo Y. and Dooley K.J. 1992), (Smith A. E. 1994), (Stutzle T. 1995), (Cheng C. S. 1995), (Chang S. I. and Aw C. A. 1996), (Hwarng H. B. and Hubele N. F. 1993b), (Cheng C. S. 1997), (Guh R. S. and Tannock J. D. T. 1999), (Guh R. S. and Hsieh Y. C. 1999), (Chang S. I. and Ho E. S. 1999), (Amirhossein Amiri, S. T. A. Niaki et al. 2015). There is only one paper in application of neural network in quality control of a single non-measurable
quality characteristic (uni-attribute). That research has been done in manufacturing industry by (Su C. T. and Tong L. I. 1997).


In multi-attribute atmosphere, there are a few researches in manufacturing industries to control the quality in case of dealing with more than one correlated non-measurable quality characteristics done by (Larpkiattaworn S. 2003), (Abbasi Babak 2007), (Niaki S. T. A. and Abbasi B. 2008a), (M.R. Maleki, A. Amiri1 et al. 2012), (Amiri Amir hossein, Maleki Mohammad Reza et al. 2014).

As a new domain, in some cases, It might be a combination of a set of variables and attributes which is called multi-variate-attribute quality control. No study on this area has been done so far regarding the application of neural netwoek, but author of this thesis has developed a new method for this domain. (Niavarani M.R. 2014)
2.4.2. **Application of neural network to analyse service in service sectors**

In this area, Researchers have focused on application of neural network to analyse service quality which has been researched in different service sectors such as transportation, restaurant, library, Bank, certification provider, education sector by (Ravi S. Behara, Warren W. Fisher et al. 2002), (Mahapatra and 2006), (Concepción Garrido, Rocío de Oña et al. 2014), (Aisyah Larasatia, Camille DeYongb et al. 2012), (S.S. Mahapatra and Khan 2007),(Anand Prakash, R.P. Mohanty et al. 2011), (Chang-long 2009), (Mir Fakhroddini, Taheri Demne et al. 2010), (Wang Ping, Yan Taishan et al. 2012), (Kailash Chandra Mishra and Das 2015)

2.4.3. **Application of neural network to analyse service in Health care**

There are 2 articles on application of neural network to analyse service in health care. Anand and Mohanty (Anand Prakash and Mohanty 2012) have proposed that service quality for healthcare must rest on a conceptual and operational definition in order to deal with the subject of managing service quality in the sector. It is found that SERVPREF based neural network out-performed the SERVQUAL based neural networks while predicting service quality for both patients and attendants, who are two important stakeholders in healthcare. The study was conducted in a multi-speciality hospital in
Bhubaneswar by using artificial neural networks (ANN) and with a sample of lower and middle income social class.

Carlucci and Renna (Daniela Carlucci, Paolo Renna et al. 2013) have proposed the use of Artificial Neural Network (ANN) as a knowledge discovery technique for identifying the service quality factors that are important to outpatient. An ANN model is developed on data from a panel of outpatients of public healthcare services. The empirical application of the ANN to the Italian context of public healthcare ambulatories shows that the relationship between doctors and outpatient (i.e. “Attention from medical staff”; “Clarity and completeness of information and explanations provided by healthcare professionals”; “Respect of privacy”) strongly affects the outpatient satisfaction.

In sum, this chapter reviewed service quality concepts, and relevant factors, and then discussed different proposed service quality measurement models (e.g., SERVPREF) in the literature. Afterwards, an overview of the service quality models applications in the healthcare sector is provided. Lastly, previous applications of neural network models for either of quality control or service analysis are presented.
Chapter 3
Research Model and Hypothesis
CHAPTER 3 – RESEARCH MODEL AND HYPOTHESIS

3. Research Model and Hypothesis

In this chapter, the used research method for this thesis is detailed. Especially, research questions and problems, as well as research objectives are described.

3.1. Introduction

This study investigates the application of Artificial Neural Network (ANN) in monitoring quality of service transaction as a dynamic and real-time control and forecasting system. To achieve this objective, the research will develop and test ANN model for control and forecasting service quality in the healthcare industry. This industry is chosen as one of the most critical servicing industry in terms of consequence of error.

3.2. Knowledge Gap and Problem Statement

In spite of considerable growth of service quality methods, there are some deficiencies in the scholarly works categorized below:
Firstly, while there have been applications of service quality models in the healthcare industry (M. Sadiq Sohail 2003) (Eleuch 2011) (Mohsin Muhammad Butt and Run 2010) (Aaron A. Abuoisi and Atinga 2013), as discussed in the earlier chapters, measuring service quality in the healthcare context is both complex and vital problem (Panchapakesan Padma, Chandrasekharan Rajendran et al. 2010), thus, there is a need to apply more recent and sophisticated tools for it.

Secondly, all proposed methods focus on attribute quality characteristics that are evaluated in the form of some subjective questions for taking customer perception of responsiveness, empathy, reliability and etc. However, there are some variable quality characteristics (objective questions) that can be measured and stated by a numerical value. For instance, time of delivered service can be measured and stated on the basis of minutes. More critical case is that there is a combination of these two types of correlated quality characteristics that are supposed to be evaluated and analyzed simultaneously. It is clear that the current statistical analysis techniques are not able to do this sort of studies.

Thirdly, these sorts of models are known as “static” methods due to their nature in which need to have a set of data at one time to be analyzed. A periodical analysis can be performed in a regular base (e.g. monthly, 6 monthly, yearly and etc.). In this type of analysis, it is not possible to monitor service quality continuously and the best application of them is to do some comparison between different periods, whereas, in Dynamic methods, quality of delivered service can be monitored at any time.
In addition to the aforementioned items, as nature of static methods, we need to have a large number of data to perform some useful and reliable study and analysis. In some cases, this volume of data is not accessible to use e.g. non-frequent or time-consuming services. However, in dynamic methods, even if we have one sample, we can evaluate service quality.

Last, but not least, these current types of models are not able to tell us what will happen in future regarding existing data. Not having prediction capability, a vital drawback of the subjective models. Because, they are not statistical models designed for forecasting.

### 3.3. Research Objectives and Research Questions

This research endeavor aims to fill the identified knowledge gap by considering the following research objectives:

a) Designing and developing of a neural networks model and its application in service quality control by using a comprehensive attribute and variable quality attributes as a standard general model and also expanding the model in healthcare industries.

b) Applying neural networks as a dynamic model for forecasting service quality in order to make some proactive decisions rather than reactive ones.

In this study, three key research questions are as follows. Investigating and finding answers to these questions are critical for the healthcare industry as they present potentials of neural network models for healthcare service quality control.
1) How can we combine some high level and complex concepts like neural network as an objective model in order to evaluate and monitor service quality instead of current subjective methods?

2) Why might be feasible to replace current subjective models by neural network model?

3) If there is any probable error in network model, what is the source of error? How the error can be eliminated by investigating error sources?
Chapter 4
Methodology
CHAPTER 4 – METHODOLOGY

4. Research Model and Hypothesis

In this chapter, the used research method for this thesis is detailed. Especially, research questions and problems, as well as research objectives are described.

4.1. Neural Networks

In this chapter, and in the following sections, an overview of neural networks models, their merits and demerits are discussed. In addition, and later, a healthcare case study, and application of ANN models for this case is discussed.

4.1.1. Overview

All the previous chapters’ discussed service quality models evaluate quality of services from different perspectives but use same approach. They apply questionnaire or other data gathering tools and evaluate the quality based on subjective concepts.

Many of quality characteristics can be measured and stated as variables with numerical values. For instance, from the manufacturing point of view, internal diameter of bearing can be measured by using a micrometer and stated on the basis of millimeter. In the
service industry context, time of delivered service can be measured by clock and stated on the basis of minutes. These types of quality characteristics are called “variable characteristics”. In addition to these variables, “attribute characteristics” cannot be measured by a measurement device but categorized as a nominal (reject, accept), ordinal (bad, good, excellent), or categorical (married, single, divorced) characteristics in service industry. Products are also categorized as conforming and nonconforming products in terms of any attribute quality characteristics such as appearance, shape, performance and etc.

Considering the previous definitions, it can be argued that the majority of quality characteristics are attribute ones in service industry. For instance, even time can be converted to attribute characteristics such as on-time/off-time (nominal) or soon, on-time, late (categorical).

There have been few studies on application of the neural network models in the service industries. Moreover, most of the corresponding researchers have studied the application of neural network for control of attribute characteristics in manufacturing industries.

Artificial Neural Networks mimic biological neural networks to model and solve a variety of problems arising in forecasting, function approximation, pattern classification, clustering, and categorization (Pao Y.H. 1989).

Human brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organize its structural constituents, known as
neurons, in order to perform certain computations many times faster than the fastest digital computer in existence today (Simon Haykin 1999).

A “developing” neuron is synonymous with a plastic brain: Plasticity permit the developing a nervous system to adapt to its surrounding environment. Just as plasticity appears to be essential to the functioning of neurons as information-processing units in the human brain, so it is with a neural network made up of artificial neurons. In its most general form, a neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer (Simon Haykin 1999).

The human nervous system may be viewed as a three-stage system, as depicted in the block diagram of Figure 4. Central to system is the brain which is represented by the neural (nerve) net. That central part continually receives information, perceives it and make appropriate decisions. Two sets of arrows are shown in Figure 4; those arrow that are pointing from left to right indicate the forward transmission of information-bearing signals through the system. However, the arrows pointing from right to left signify the presence of feedback in the system. The receptors convert stimuli from the human body or external environment into electrical impulses generated by the neural net into discernible responses as system outputs (Simon Haykin 1999).
It is estimated that there are approximately ten billion neurons in the human cortex, and sixty billion synapses or connections. Synapses are elementary structural and functional units that mediate the interaction between neurons. Axons, the transmission lines, and dendrites, the receptive zones, constitute two types of cell filaments that are distinguished on morphological ground; an axon has a smoother surface, fewer branches, and greater length, whereas a dendrite (so-called because of its resemblance to a tree) has irregular surface and more branches. Figure 5 illustrates the shape of a pyramidal cell, which is one of the most common types of cortical neurons. Like many other types of neurons, it receives most of its inputs through dendritic spines; see the segment of dendrite in the insert in figure 5 for detail (Simon Haykin 1999).
From the technical point of view, the block diagram of Figure 6 shows the model of neuron, which forms the basis for designing artificial neural networks. Three basic elements of the neural model are (Simon Haykin 1999):

1. A set of synapses or connecting links, each of which is characterized by a weight or strength of its own. Specially, a signal $x_j$ at the input of synapse $j$ connected to neuron $k$ is multiplied by a synaptic weight $w_{kj}$. 

Figure 5. the pyramidal cell adopted from (Simon Haykin 1999)
2. An *adder* for summing the input signals, weighted by respective of the neuron; the operation described here constitute a *linear combiner*.

3. An *activation function* for limiting the amplitude of the output of a neuron.

![Neuron model diagram](image)

Figure 6 — nonlinear model of neuron adopted from (Simon Haykin 1999)

The neuronal model in Figure 5 also indicates an externally applied *bias*, denoted by $b_k$. The bias has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively.

Using the mathematical and formal notations, we can describe a neuron $k$ by writing the following equations:

$$
\sum_{j=1}^{m} w_{jk} x_j = u_k
$$

(Eq. 1)

$$
b_k
$$

(Eq. 2)
\[ y_k = \Phi(u_k + b_k) \]

In equations (Eq.1) and (Eq.2), parameters \( x_1, x_2, \ldots, x_m \) are the input signals; \( w_{k1}, w_{k2}, \ldots, w_{km} \) are the synaptic weights of neuron \( k \). In addition, \( u_k \) is the linear combiner output due to the input signals; \( b_k \) is the bias; \( \Phi() \) is the activation function; and \( y_k \) is the output signal of the neuron.

The activation function defines the output of a neuron in terms of the induced load field \( \Phi \). There are different activation function such as Threshold function, Piecewise-linear function, sigmoid function and etc. which are applied for different type of outputs (Simon Haykin 1999).

For more clarification, consider the following simple illustration in which the models are represented as a graphical network in Figure 7. In this figure, each node is referred to as a neuron. The three main types of neurons are original predictor (input signal) \( x_j \), derived predictor \( z_j \) and response \( y_j \) neurons. The network’s arrows represent the dependencies between neurons. In addition, the set of derived predictors are arranged in a set of layers which are called hidden layers.
Figure 7 — Different types of Neurons

In terms of structuring of a network, there are different classes of network architectures including single-layer feed-forward networks, multi-layer feed-forward networks, and recurrent networks (Simon Haykin 1999).

After structuring a neural network, that network needs to be trained based on some different circumstances (different inputs and different outputs) to be able to forecast the output for future inputs with an acceptable error level through an ongoing modification process.
A crucial property of a neural network that has significant implications is the ability of the network to learn from its environment, and to improve its performance through learning. Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by the procedure/algorithm in which the parameter changes take place. There are different types of learning processes including Error-correction learning, Memory-based learning, Hebbian learning, Competitive learning, Boltzmann learning, unsupervised learning, supervised learning and etc (Simon Haykin 1999).

4.1.2. Merits and Demerits

Generally, the use of neural networks offers the following useful properties and capabilities (Simon Haykin 1999):

1. **Nonlinearity.** An artificial neuron can be linear or nonlinear.

2. **Input-Output Mapping.** The network is presented with an example picked at random from the set, and the synaptic weights (i.e., free parameters) of the network modified to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion.
3. *Adaptivity.* Neural networks have a built-in capability to adapt their synaptic weight to changes in the surrounding environment.

4. *Evidential Response.* In the context of pattern classification, a neural network can be designed to provide information not only about which particular pattern to *select*, but also about *confidence* in the decision made that is used to reject ambiguous pattern.

5. *Contextual information.* Every neuron in the network is potentially affected by the global activity of all other neurons in the network. Consequently, contextual information is dealt with naturally by a neural network.

6. *Fault Tolerance.* A neural network, implemented in hardware form, has the potential to be inherently fault tolerant, or capable of robust computation, in the sense that its performance degrades gracefully under adverse operating conditions.

7. *VLSI Implementability.* The massively parallel nature of a neural network makes it potentially fast for the computation of certain tasks. This same feature makes a neural network well suited for implementation using *very-large-scale-integrated* (*VLSI*) technology.

8. *Uniformity of Analysis and Design.* Basically, neural network enjoy universality as information processors. We say this in the sense that the same notation is used in all domains involving the application of neural network.
9. **Neurobiological Analogy.** The design of a neural network is motivated by analogy with the brain, which is a living proof that fault tolerant parallel processing is not only physically possible but also fast and powerful.

In terms of their application in quality control, the neural network models have the following advantages:

1. No restriction for type of input and output variables (variable, attribute, their combination)

2. No assumption for statistical distribution of variables and their dependency as well

3. No limitation for number of inputs and outputs

4. No need to have a large sample size of data. In implementation phase, the model can be used with even one sample.

5. Efficient to fit and predict (even for dynamic application)

Regardless of all aforementioned merits, a neural network model has the following drawbacks (Trevor Hastie et al. 2001):

1. Trial and error element to building good models (In training phase)

2. It is hard to interpret what is happening in the model (Black Box) and people only see the inputs and outputs
3. According to what is known as over-fitting, the iterative model fitting will often over-fit on the training dataset, unless steps are taken to alleviate this.

4. Model performance relates to starting input values and parameters.

5. In terms of variable scaling, neural network models fit better if all variables are on a similar scale.

4.2. Case Study

In the remaining parts of this chapter, our modelling and approach toward a healthcare industry case study is presented.

4.2.1. Introduction

In order to evaluate the application of designed quality control model, a healthcare case study is studied and analyzed in this thesis. There are some different services that can be nominated for such a case study e.g. education, public transportation, banking, healthcare, and so forth. Among these and comparing it with the other service industries, healthcare industry deals with many challenges, while they are concurrently under public scrutiny as consumer demands escalate. Medical care quality control and improvement is expected to enhance confidence in the medical community providing safe and effective patient care. Note that poor quality in patient care processes can run the spectrum from minor dietary issues to patient morbidity and fatality. It seems that applying a biological-origin concept in health care industry would be interesting. (Ginny W. Frings and Laura
Health care is the most crucial service industry because of its nature of zero
tolerance for mistakes and potential for reducing medical (Y.H. Kwak and Anbari 2006).
Health care is the largest service industry accounting for 17 percent of the US GDP ahead
of education at 10 percent (Richard C. Larson 2009). There are about 7,500 hospitals in
the United States but about 4,000 institutions of higher education (Richard C. Larson
2010).

The Commonwealth Fund, in its annual survey, "Mirror, Mirror on the Wall", compares
the performance of the health care systems in Australia, New Zealand, the United
Kingdom, Germany, Canada and the U.S. The Organization for Economic Co-operation
and Development (OECD) also collects comparative statistics, and has published brief
country profiles that is shown in Table 2 (The Commonwealth Fund 2007, Organization
for Economic Co-operation and Development 2008, Wikipedia 2010). According to this
table, over 17% of Australian government revenues are spent on healthcare costs.
<table>
<thead>
<tr>
<th>Country</th>
<th>Per capita expenditure on health (USD)</th>
<th>Healthcare costs as a percent of GDP</th>
<th>% of government revenue spent on health</th>
<th>% of health costs paid by government</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>3,137</td>
<td>8.7</td>
<td>17.7</td>
<td>67.7</td>
</tr>
<tr>
<td>Canada</td>
<td>3,895</td>
<td>10.1</td>
<td>16.7</td>
<td>69.8</td>
</tr>
<tr>
<td>France</td>
<td>3,601</td>
<td>11.0</td>
<td>14.2</td>
<td>79.0</td>
</tr>
<tr>
<td>Germany</td>
<td>3,588</td>
<td>10.4</td>
<td>17.6</td>
<td>76.9</td>
</tr>
<tr>
<td>Japan</td>
<td>2,581</td>
<td>8.1</td>
<td>16.8</td>
<td>81.3</td>
</tr>
<tr>
<td>Norway</td>
<td>5,910</td>
<td>9.0</td>
<td>17.9</td>
<td>83.6</td>
</tr>
<tr>
<td>Sweden</td>
<td>3,323</td>
<td>9.2</td>
<td>13.6</td>
<td>81.7</td>
</tr>
<tr>
<td>UK</td>
<td>2,992</td>
<td>8.4</td>
<td>15.8</td>
<td>81.7</td>
</tr>
<tr>
<td>USA</td>
<td>7,290</td>
<td>16.0</td>
<td>18.5</td>
<td>45.4</td>
</tr>
</tbody>
</table>

Table 2: brief country health care profiles

The Institute of Medicine’s definition of quality has proved of enduring usefulness: “Quality is the extent to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge” (Mark R. Chassin 1998).

Some operational inefficiencies are associated with the direct medical service delivery process. Others are associated with the administrative, logistical, and operational side of the healthcare delivery system. Both areas can benefit from systematic process innovation activities (Henk de Koning, John P. S. Verver et al. 2006).
A large number of different attributes, and, variables quality characteristics can be considered in the healthcare industry which can be monitored, predicted, and improved. Sehwail et al. (Loey Sehwail and Camille De Yong 2003, Richard Stahl R, Schultz B et al. 2003) posit that the quality characteristics in health care can be classified into four categories:

- Service level (e.g. access to care, wait time, service time);
- Service cost (e.g. cost per unit of service, labor productivity);
- Customer satisfaction (e.g. patient or family, referring physician, employee);
- Clinical excellence (e.g. guidelines for medication or treatment, standard procedures for patient monitoring)

From a different perspective, Elizabeth A. McGlynn et al. (Elizabeth A. McGlynn, Steven M. Asch et al. 2003) proposed different quality indicators in three types of care including preventive, acute and chronic, and, in the four different functions including screening, diagnosis, treatment and follow up. In an analytical paper published by “The Quality in Australian Health Care Study (QAHCS)”, Ross McL Wilson et al. analyzed the cause of adverse events resulting from health care in Australia from different categories like human error categories, delay categories, treatment categories, and investigation categories (Ross McL Wilson, Bernadette T Harrison et al. 1999).

Length of Stay (LoS) in healthcare systems has been identified as an important performance measure in the hospitals and healthcare systems (Michael Fine, Hugh M
Pratt et al. 2000). For instance, reduction of LoS is considered to be one of the six performance measures in UK. In UK, healthcare managers’ performance depends on some performance indicators, including LoS (Aileen Clarke and Rebecca Rosen 2001). In a similar way, National Health Insurance Program in Taiwan emphasizes on management of patients’ LoS (Tsang-Hsiang Cheng and Paul Jen-Hwa Hu 2009).

A patient’s LoS spans different disease states or recovery phases and is often influenced by the severity or acuity of the patient’s medical condition and pace of recovery. Although LoS can generally be stratified for patients diagnosed with the identical disease or who receive the same surgical procedure, the actual LoS inevitably varies. Such variance requires the need for effective and sophisticated methods for prediction of LoS. With having some effective predictions, the health-care institutions and clinicians can improve their decisions about patient management and resource allocations (J. Grigsby, R. Kooken et al. 1994).

There have been attempts to predict LoS. As an example, the Columbia-Presbyterian Medical Center investigated LoS data to identify essential factors that can cause an extended LoS (W. E. Pofahl, S. M. Walczak et al. 1998). Some other previous researches used a classification approach to generate early alerts with respect to a target LoS range. For example, Buchman et al. (T. G. Buchman, K. L. Kubos et al. 1994) predict chronicity in a surgical intensive care unit by classifying patients’ LoS in accordance with a recommended seven-day norm. In response to the need for effective resource planning and cost containment, Mobley et al. (B. A. Mobley, R. Leasure et al. 1995) predict the LoS of patients receiving post coronary care over the range of 1–20 days. Frye et al. (K.
E. Frye, S. D. Izenberg et al. 1996) use a computational technique to predict whether the LoS of patients suffering from burns will fall within a one-week period.

### 4.2.2. ANN Model for Emergency Department of Private Hospital

This case study focuses on LoS at an emergency department. Relatedly, our assumptions, and data collection and model development steps are described in the next sections. Furthermore, some discussions also are provided on the ANN models’ performance.

#### 4.2.2.1. Assumptions and Dataset

We consider Length of Stay (or LoS), which is called waiting time, at an emergency department of Private hospital. The process of caring patients in the emergency department has mapped in Figure 8.

---

Figure 8. Process Map in Emergency Department
Generally, patient waiting time at emergency department as a dependent variable is depended by some other independent variables such as time of arrival, age of patients and etc. A full list of these dependent and independent variables are listed in Table 3. In this table, there are two dependent variables that are denoted by Y1 and Y2. The first variable Y1 is patient waiting time, whereas the second variable Y2 is patient waiting time deviation which is considered as deviation of actual waiting time from standard waiting time (Actual waiting time-standard waiting time). Based on the regulation of the private hospital (that provided the dataset), standard waiting time is determined as “less than 5”, “less than 10 minutes”, “less than 30 minutes”, “less than 60 minutes” and 60 minutes for Triage Category (Acuity) 1, 2, 3, 4 and 5, respectively.

The reason for using variable Y2 as a parallel performance indicator is that sometimes waiting time is more because of the nature of the case which is not necessarily worse than a less critical cases which takes less time. So, the second variable Y2 plays an important role like a standardized variable Y1 which help to compare them together.

The independent variable that are denoted by Xs (e.g., X1, X2) are weighted that are in range [1,2,3,4,5]. These weights are provided by the private hospital to distinguish the importance, and effects of each of them on variables Y1 and Y2. Thus, the higher weighted for those Xs variables, the more they will affect variables Y1 and Y2. Lastly, in the last column, the operational range for each of the independent variables are shown. For example, age of the patients is defined to be within the following range [0 year-110 years].
<table>
<thead>
<tr>
<th>Variable</th>
<th>Name</th>
<th>Weight</th>
<th>Operational Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y1</td>
<td>Waiting time</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Y2</td>
<td>Waiting time deviation</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>X1</td>
<td>Age</td>
<td>2</td>
<td>0-110</td>
</tr>
<tr>
<td>X2</td>
<td>Gender</td>
<td>1</td>
<td>M/F</td>
</tr>
<tr>
<td>X3</td>
<td>Week day of Arrival</td>
<td>2</td>
<td>Mon-Sun</td>
</tr>
<tr>
<td>X4</td>
<td>Date and Time of Arrival</td>
<td>2</td>
<td>dd/mm/yyyy 00:00</td>
</tr>
<tr>
<td>X5</td>
<td>Mode of Arrival</td>
<td>3</td>
<td>From excel</td>
</tr>
<tr>
<td>X6</td>
<td>Triage Category (Acuity)</td>
<td>4</td>
<td>1,2,3,4,5</td>
</tr>
<tr>
<td>X7</td>
<td>Provisional Diagnosis</td>
<td>3</td>
<td>Sheet4-rows (840)</td>
</tr>
<tr>
<td>X8</td>
<td>Diagnosis category</td>
<td>4</td>
<td>Sheet5-rows (49)</td>
</tr>
<tr>
<td>X9</td>
<td>ED Bed Occupancy</td>
<td>4</td>
<td>1,…,38</td>
</tr>
<tr>
<td>X10</td>
<td>%ED Bed Occupancy</td>
<td>4</td>
<td>[0-100]</td>
</tr>
<tr>
<td>X11</td>
<td>Patients Awaiting Bed or ED Admit</td>
<td>4</td>
<td>1..25</td>
</tr>
<tr>
<td>X12</td>
<td>%Patients Awaiting Bed or ED Admit</td>
<td>4</td>
<td>[0-100]</td>
</tr>
<tr>
<td>X13</td>
<td>Arrivals in Hr Prior</td>
<td>5</td>
<td>0-13</td>
</tr>
<tr>
<td>X14</td>
<td>Seen Date and time</td>
<td>1</td>
<td>dd/mm/yyyy 00:00</td>
</tr>
<tr>
<td>X15</td>
<td>Seen Time (in second)</td>
<td>1</td>
<td>0-3600*24</td>
</tr>
<tr>
<td>X16</td>
<td>Date and Time of Discharges</td>
<td>2</td>
<td>dd/mm/yyyy 00:00</td>
</tr>
<tr>
<td>X17</td>
<td>Time of Discharges (in second)</td>
<td>2</td>
<td>0-3600*24</td>
</tr>
<tr>
<td>X18</td>
<td>Departures in HR Prior</td>
<td>3</td>
<td>0-14</td>
</tr>
<tr>
<td>X19</td>
<td>Admitted</td>
<td>2</td>
<td>Yes/No</td>
</tr>
<tr>
<td>X20</td>
<td>Dr Hr</td>
<td>3</td>
<td>2-6</td>
</tr>
<tr>
<td>------</td>
<td>-------</td>
<td>----</td>
<td>-------</td>
</tr>
<tr>
<td>X21</td>
<td>Nursing Hr</td>
<td>2</td>
<td>4-11</td>
</tr>
<tr>
<td>X22</td>
<td>Clerical Hours</td>
<td>2</td>
<td>1,2,2.5,3</td>
</tr>
<tr>
<td>X23</td>
<td>% Dr last hr shift</td>
<td>3</td>
<td>[0-100]</td>
</tr>
<tr>
<td>X24</td>
<td>Is ICU admission?</td>
<td>3</td>
<td>Yes/No</td>
</tr>
</tbody>
</table>

Table 3. Model input and output characteristics

### 4.2.2.2. Designing and programming ANN models

Designing ANN models follows a number of systemic procedures. For this case study, the following five steps have been undertaken: collecting data, pre-processing data, building the network, train the network, and test / validation of the model. These steps are described in below.

#### 4.2.2.2.1. Data Collection

Collecting and preparing sample data is the first step in designing ANN models. In the first step 27,253 records of sample patient’s process in ED have been gathered from 1/1/2013 to 31/12/2013. For each of these records, twenty-four independent variables Xs (e.g., X1, X2) as well as the waiting time variable Y1 have been recorded.
4.2.2.2. Data pre-processing

After data collection, a data pre-processing procedure is conducted to model the network more efficiently. This procedure aims to solve the problem of missing data. Some SQL commands are run to solve the missing values and also transform the categorical variables (i.e. triage mode) into numerical categories (i.e. 1,2,3,...). This process has been implemented using SQL command, and the used commands are provided in the Appendix section. This procedure finally filters the data and the final set of data includes about 27024 records.

4.2.2.2.3. Building the Network

At this stage, various parameters of the network as the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function, are specified.

For this case study, two hidden layers are used for the network that have been suggested to suffice and avoid over-fitting (Karsoliya 2012). Two cases with ten and twenty hidden layers are used.

As per the transfer functions, linear (purelin), Hyperbolic Tangent Sigmoid (logsig) and Logistic Sigmoid (tansig) functions as the MATLAB build-in functions are used for this case study. The graphical illustration and mathematical form of the functions are shown in Figure 9.
4.2.2.2.4. Training the Network

During the training process, the weights are adjusted in order to make the actual outputs (predicted) close to the target (measured) outputs of the network. The used weights for the input variables are shown in Table 3. As an alternative, the network has been trained without considering the weights, which is labeled as unchanged weights in the analysis. In the scenario of incorporating the weights in Table 3, 70% (randomly selected) of all record (27024 records) are used for training the network.

In order to compare and examine the effectiveness of the provided weights by experts, ANNs with unchanged weights (i.e. weights are determined by MATLAB ANN toolbox) are also developed. These comparisons can illustrate which type of weights (weights by experts vs. by software/MATLAB) in ANNs tend to have higher performance levels (e.g. lower error level, low MSE).
When the network weights and biases are initialized, the network is ready for training (MATLAB Website). The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance (in MATLAB, it is defined by the network performance function “net.performFcn”). The default performance function for feedforward networks is Mean Square Error (MSE)---the average squared error between the network outputs and the target outputs.

Different training functions (e.g. Levenberg-Marquardt) can be applied for ANN models (some of such models can be found at MATLAB Website). For problems with large datasets, it has been recommended to use either of the following training functions:

<table>
<thead>
<tr>
<th>Function Name</th>
<th>Graphical Illustration</th>
<th>Mathematical form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td><img src="image1.png" alt="Linear Graph" /></td>
<td>$f(x) = x$</td>
</tr>
<tr>
<td>Hyperbolic Tangent Sigmoid</td>
<td><img src="image2.png" alt="Hyperbolic Tangent Sigmoid Graph" /></td>
<td>$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$</td>
</tr>
<tr>
<td>Logistic Sigmoid</td>
<td><img src="image3.png" alt="Logistic Sigmoid Graph" /></td>
<td>$f(x) = \frac{1}{1 + e^{-x}}$</td>
</tr>
</tbody>
</table>

Figure 9. The three common transfer functions of ANN modeling
Bayesian Regularization (trainbr) or Scaled Conjugate Gradient (trainscg), respectively (MATLAB Website).

### 4.2.2.2. Performance Analysis of ANN Models

Once training process is completed, its performance can be analyzed. Generally, some portions of a dataset are used for training, validation and test performance. In this MATLAB program for this project, 85%, 10% and 5% are respectively used for training, validation and test. A well-developed ANN’s plot of the training errors, validation errors, and test errors is shown in below. In this example, the result is reasonable because of the following considerations:

- The final mean-square error is small.
- The test set error and the validation set error have similar characteristics.
- No significant over-fitting has occurred by iteration 17 (where the best validation performance occurs) as the validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some over-fitting might have occurred.

An example graph of ANN validation, training and test performance; produced by MATLAB is shown in Figure 10.
The next step in validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice.

The three plots in below (Figure 11) represent the training, validation, and testing data of an example dataset. The dashed line in each plot represents the perfect result — outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.
For this example, the training data indicates a good fit. The validation and test results also show R values that greater than 0.9. The scatter plot is helpful in showing that certain data points have poor fits. For example, there is a data point in the test set whose network output is close to 35, while the corresponding target value is about 12.

Figure 11. Regression plot of training, validation and test datasets of a sample dataset

All the formerly graphs and training, validation and test performance graphs as well as the number of errors (both over-prediction and under-prediction) are stored. These graphs
and performance values are analyzed in the next step which is described in the following section.

In sum, in this chapter, merits, drawbacks, and general features of the neural networks models (as research model of this thesis) are discussed. Moreover, the case study which mainly focuses on LoS at an emergency department is described, and also, a neural network model is built for it.
Chapter 5
Results
CHAPTER 5 – METHODOLOGY

5. Results

In this chapter, and in the following sections, an overview of neural networks models, their merits and demerits are discussed. In addition, a healthcare case study on which the proposed model has been applied is discussed.

5.1. Meta Algorithm for Influential Input Variables Identification

As there are a large number of possibly influential factors on waiting time in ED (i.e. the list of variables in Table 1), I elaborate a meta-algorithm to find the best subset of the influential factors or independent variables (i.e. X1-X24 in Table 3 of Chapter 4) that appear to be more reliable and robust predictors of the waiting time of patients in ED. The algorithm is illustrated and shown in below:

1. Data preparation:
   - Collecting data
   - Pre-processing (Appendix A)

2. Select a subset of factors among [X1...X24], and call it set “S”. Using this set, build and test ANN for a scenario:
   - Build ANN model
   - Train it
- Test its performance using different performance measures

3. **Update set “S” (i.e. select another subset of \([X_1, \ldots, X_{24}]\)):**
   - Go back to step “2” if still more scenarios need to be examined
   - Stop the algorithm if enough number of scenarios have been investigated.

When all steps for building ANN of a subset “S” of the all independent variables or factors (e.g. \([X_1, X_2, X_3, X_4, X_5]\)) are conducted and their results are finished, then the next step is to continue the loop or stop. This decision is required as with the high number of possible scenarios (i.e. selection of 1<\(n\)<=24 variable among 24 factors), it is computationally impossible to build/store ANNs for all possible scenarios.

If the decision is to stop the algorithm, then all the obtained results are stored and analyzed as described in the next sections of this chapter. However, in the case of continuing the loop, a new subset “S” (e.g. \([X_1, X_2, X_3, X_5, X_7]\)) is generated and all the formerly described procedures for building and analysing its corresponding ANN model are repeated.

In order to investigate all possible scenario regions (i.e. to examine ANN models of subsets with different size), we have executed the meta-loop algorithm for the subsets of 24 factors with the following varying sizes:

- Running the meta-loop for the subsets that include only five variables (e.g. \([X_1, X_2, X_3, X_4, X_5]\)) for 1000 or more iterations (i.e. or scenarios or subset “S”).
• Running the meta-loop for subsets that include only ten variables (e.g. [X1, X2, X3, X4, X5, X10, X11, X12, X13, X17]) for 1000 or more iterations (i.e. or scenarios or subset “S”).

• Running the meta-loop for the subsets that include only fifteen variables (e.g. [X1, X2, X3, X4, X5, X10, X11, X12, X13, X17, X19, X20, X21, X22, X23]) for 1000 or more iterations (i.e. or scenarios or subset “S”).

• Running the meta-loop for the subsets that include only seventeen variables (e.g. [X1, X2, X3, X4, X5, X7, X8, X10, X11, X12, X13, X17, X19, X20, X21, X22, X23]) for 1000 or more iterations (i.e. or scenarios or subset “S”).

• Running the meta-loop for the subsets that include only nineteen variables (e.g. [X1, X2, X3, X4, X5, X7, X8, X10, X11, X12, X13, X14, X17, X18, X19, X20, X21, X22, X23]) for 1000 or more iterations (i.e. or scenarios or subset “S”).

5.2. Systematic Analysis of Meta Algorithm Results

By conducting some experiments using MATLAB and the meta algorithm that was described in the former section, the following results are obtained. In addition to all graphs, the following table was written and stored in an Microsoft Excel file. These results are generated by using 27024 records of data about the patients and their waiting time, provided by the hospital administration staff and managers.

The generated results in the Excel file includes 6149 records of data (i.e. or scenarios or subset “S”) for the following fields:
○ Subset “S”, e.g. [X1,X2,X3,X4,X5]

○ Transform function: The type of transfer function that was used when calculating a layer output from its net input, e.g. tansig, purline;

○ Output type: waiting time (Y1) or waiting time deviation (Y2) that were defined before;

○ Number of neurons that can be either ten or twenty;

○ Number of positive errors: If the predicted waiting time (i.e. output) is greater than the actual waiting time, then over-prediction happens. The number of these errors when all 27024 available data were used and predictions are made for them based on the model.

○ Number of negative errors: The number of under-predictions that happened when predicting 27024 available data;

○ Regression slope: the slope of regression plot (regression between the actual waiting time and the prediction values);

○ Offset of Regression: The offset of regression;

○ Train performance: The Mean Square Error (MSE) of training performance, normalized in [0,1] interval;

○ Validation performance: Normalized MSE error of validation;

○ Test performance: Normalized MSE error of test performance.
Some of these generated data are provided in Table 4 in below:

<table>
<thead>
<tr>
<th>Subset “S”</th>
<th>Transform Function</th>
<th>Output Type</th>
<th>Weight Type</th>
<th>Number of Neurons</th>
<th>Number of Positive Error (Output Target)</th>
<th>Number of Negative Error (Output Target)</th>
<th>Regression Slope</th>
<th>Offset of Regression</th>
<th>Train Performance</th>
<th>Validation Performance</th>
<th>Test Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1, X2, X3, X4, X5</td>
<td>purelin</td>
<td>Y2</td>
<td>Adjusted Weight</td>
<td>10</td>
<td>18040</td>
<td>8984</td>
<td>0.010</td>
<td>2834.349</td>
<td>0.989</td>
<td>0.989</td>
<td>0.989</td>
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<tr>
<td>X1, X2, X3, X4, X6</td>
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<td>Y1</td>
<td>Unchanged Weight</td>
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<td>18032</td>
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<td>0.988</td>
<td>0.988</td>
</tr>
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<td>Y1</td>
<td>Adjusted Weight</td>
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<td>8311</td>
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<td>0.987</td>
<td>0.990</td>
</tr>
<tr>
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<td>Y1</td>
<td>Unchanged Weight</td>
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<td>8329</td>
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<td>3102.187</td>
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<td>0.989</td>
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</tr>
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<td>Y2</td>
<td>Unchanged Weight</td>
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<td>18703</td>
<td>8321</td>
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<td>3105.607</td>
<td>0.988</td>
<td>0.989</td>
<td>0.988</td>
</tr>
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<td>logsig</td>
<td>Y1</td>
<td>Adjusted Weight</td>
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<td>26802</td>
<td>222</td>
<td>-0.001</td>
<td>12766.760</td>
<td>0.828</td>
<td>0.827</td>
<td>0.829</td>
</tr>
<tr>
<td>X1, X2, X3, X4, X13</td>
<td>logsig</td>
<td>Y2</td>
<td>Adjusted Weight</td>
<td>10</td>
<td>26802</td>
<td>222</td>
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<td>logsig</td>
<td>Y1</td>
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<td>222</td>
<td>-0.001</td>
<td>12766.701</td>
<td>0.828</td>
<td>0.829</td>
<td>0.828</td>
</tr>
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<td>logsig</td>
<td>Y2</td>
<td>Unchanged Weight</td>
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<td>12765.820</td>
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<td>0.827</td>
<td>0.826</td>
</tr>
</tbody>
</table>

Table 4: Sample results of running the meta-algorithm.
As explained before, for each subset “S” of the independent factors, three types of graphs are generated: (a) validation, training and test performance (b) regression plot (c) over-prediction and under-prediction errors histogram. Some samples graphs of those figures are presented in Figure 9 in below.

![Graphs](image)

**Figure 12:** Samples of generated graphs by MATLAB program

In order to systematically analyze the results and graphs, the following steps are conducted. Firstly, for each scenario, the generated results from meta-algorithm
execution, that include different performance measures are ordered according to a particular performance measure. For instance, for each scenario, all the generated results are ordered according to the “Train Performance” field. Then, the top twenty scenarios with the highest performance values (e.g. low MSE of train performance) are selected and analyzed. Then, in the next step, any pattern of repetition of particular factors (e.g. X1, X5) among the identified top scenarios is examined. Such patterns imply that those scenarios with the observed pattern tend to have correlation/association with the corresponding ANN models with the used performance measure.

In addition to identifying the patterns in scenarios, the corresponding graphs of the top twenty scenarios are examined. By this detail investigation, I make sure that my findings from the results dataset file are robust. Furthermore, any possible additional implication is captured and discussed.

5.3. Meta Algorithm Results

At first, I focus on finding ANN models that are associated with the lowest number of positive and negative errors (output-target). Thus, I examine the top twenty scenarios with the lowest number of these errors are presented in the following Tables (Table 5 and Table 6).

According to the results in Table 5, ANN models that include a large portion of the all twenty independent variables tend to have a lower number of over-predictions. For instance, the following scenario belongs these models, and it encompasses twenty
independent variables: \([X1 ; X2 ; X3 ; X4 ; X5 ; X6 ; X7 ; X8 ; X10 ; X11 ; X12 ; X13 ; X14 ; X15 ; X16 ; X17 ; X18 ; X19 ; X20]\). Furthermore, these ANN models tend to have high number of positive errors (i.e. more than 50% of the total number of data, 27024). In the same line, these scenarios have high MSE errors (more than 0.9 in the \([0,1]\) normalized scale). Thus, ANN models appear to have more tendency toward over-prediction of the waiting time measure (in comparison to under-prediction).

The ANN models in Table 6 are similar to Table 5 as they present those ANN models that have both output types (Y1 and Y2) and weighted/unchanged weights. However, in contrast to ANN models with low over-prediction, the models with low negative errors (Table 6) found to be with only few factors, e.g. \([X1 ; X2 ; X4 ; X5 ; X6 ;]\). The models with X1, X2, X4, X5 and X6 as independent variables seem to have lowest under-prediction number of errors. Moreover, these ANN models have lower MSE performance errors (about 0.80 in the scale \([0,1]\)) than those with a lower over-predictions feature (Table 5).

Contemplating both Tables 5 and 6, the following overall implication about the ANN models with a low over/under prediction error:

- Those ANN models that mainly (i.e. they have few, e.g. five factors) include X1 (Age), X2 (Gender), X4 (Date and Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category) appear to result in a lower over-prediction as well as under-prediction error.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Transform function</th>
<th>Output type</th>
<th>Weight type</th>
<th>Number of neuron</th>
<th>Number of positive errors(output-target)</th>
<th>Number of negative errors(output-target)</th>
<th>Regression slope</th>
<th>Offset of Regression</th>
<th>Train Performance</th>
<th>Validation Performance</th>
<th>Test Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1 ; X2 ; X3 ; X4 ; X5 ; X6 ; X8 ; X9 ; X10 ; X11 ; X12 ; X13 ; X14 ; X15 ; X16 ; X17 ; X18 ; X19 ; X20 ; X21 ;</td>
<td>purelin</td>
<td>Y2</td>
<td>Adjusted Weight</td>
<td>10</td>
<td>15700</td>
<td>11324</td>
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<td>1927</td>
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<td>0.992</td>
<td>0.992</td>
</tr>
<tr>
<td>X1 ; X2 ; X3 ; X4 ; X5 ; X6 ; X8 ; X9 ; X10 ; X11 ; X12 ; X13 ; X14 ; X16 ; X17 ;</td>
<td>purelin</td>
<td>Y2</td>
<td>Unchanged Weight</td>
<td>10</td>
<td>15729</td>
<td>11295</td>
<td>0.29</td>
<td>1931</td>
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</tr>
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<td>purelin</td>
<td>Y1</td>
<td>Unchanged Weight</td>
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<td>Unchanged Weight</td>
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<td>Y2</td>
<td>Unchanged Weight</td>
<td>10</td>
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</tr>
<tr>
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<td>Transform function</td>
<td>Output type</td>
<td>Weight type</td>
<td>Number of neuron</td>
<td>Number of positive errors(output-target)</td>
<td>Number of negative errors(output-target)</td>
<td>Regression slope</td>
<td>Offset of Regression fit</td>
<td>Train Performance</td>
<td>Validation Performance</td>
<td>Test Performance</td>
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</tr>
<tr>
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<td>Unchanged Weight</td>
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<td>Y1</td>
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<td>Output Type</td>
<td>Weight Type</td>
<td>Number of neuron</td>
<td>Number of positive errors(output-target)</td>
<td>Number of negative errors(output-target)</td>
<td>Regression slope</td>
<td>Offset of Regression</td>
<td>Train Performance</td>
<td>Validation Performance</td>
<td>Test Performance</td>
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<td>Weight type</td>
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<td>Y2</td>
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<td>Y2</td>
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<td>11119</td>
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<td>Y2</td>
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<td>0.991</td>
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</table>

Table 5: The top twenty scenarios with the lowest number of the positive errors
<table>
<thead>
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<th>Scenario</th>
<th>Transform function</th>
<th>Output Type</th>
<th>Weight Type</th>
<th>Number of neuron</th>
<th>Number of positive errors(output-target)</th>
<th>Number of negative errors(output-target)</th>
<th>Regression slope</th>
<th>Offset of Regression</th>
<th>Train Performance</th>
<th>Validation Performance</th>
<th>Test Performance</th>
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Table 6: The top twenty scenarios with the lowest number of the negative errors
The figures related to the ANN models of scenarios in Tables 5 and 6 are presented in below as well. The top graphs show the frequency of errors when ANN models are tested against the actual data. However, the bottom graphs depict the regression plot of actual waiting time and predicted outputs by ANN models. These graphs illustrate that the ANN models perform well.

Figure 13: Samples of generated graphs; top left and bottom: X1 X2 X3 X4 X5- UnchangedWeight—Y1—10—logsig for low negative errors; top right and bottom right:
X1 X2 X3 X4 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X15 X16 X17 X18 X19 X21-
UnchangedWeight-Y2-10-purelin for low positive errors

The next Table, Table 7 shows those subsets “S” or scenarios whose ANN models have top high regression slope. That is, these ANN models perform well when their predictions are tested/validated against actual data. As shown, both types of the output/dependent variables (Y1 or Y2) and weighs (weighted/unchanged weights) found for these models. They also have “purline” as neuron transfer function and high MSE errors. These ANN models tend to have mainly a large number of the independent factors and the following factors are more common among them:

X1 (Age), X2 (Gender), X3 (Week day of Arrival), X4 (Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category), X7 (Provisional Diagnosis), X8 (Diagnosis category), X9 (ED Bed Occupancy), X10 (%ED Bed Occupancy), X11 (Patients Awaiting Bed or ED Admit) X12 (%Patients Awaiting Bed or ED Admit), X13 (Arrivals in Hr Prior), X14 (Seen Date and time), X15 (Seen Time (in second)), X16 (Date and Time of Discharges), X17 (Time of Discharges (in second)), X18 (Departures in HR Prior).
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<th>Weight type</th>
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Table 7: The top twenty scenarios with the highest regression slope

| X1 ; X2 ; X3 ; X4 ; X5 ; X6 ; X7 ; X8 ; X9 ; X10 ; X11 ; X12 ; X13 ; X14 ; X15 ; X16 ; X17 ; X20 ; X21 ; | purelin | Y2 | Unchanged Weight | 10 | 15992 | 11032 | 0.293 | 1967 | 0.992 | 0.992 | 0.991 |


The next three Tables, Table 8, 9, and 10, present the ANN models and scenarios with a low MSE error. Interestingly and as we expect, they almost share the following features:

- Similar to the former Tables and performance measures, output type and weight type (weighted and unchanged weights) do not seem to be a dominant factor.
- The ANN models with “Logsig” transform function found to have low MSE errors.
- The ANN models have a high number of positive errors (over-prediction) and a low number of negative errors (under-prediction). Thus, considering the MSE performance measures, ANN models with over-prediction seem to be the best ones.
- ANN models with few factors seem to have lower MSE errors. Also, these models include the following factors: X1 (Age), X2 (Gender), X3 (Week day of Arrival), X4 (Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category), X7 (Provisional Diagnosis), X8 (Diagnosis category).

In addition to the ANN models, examples of their corresponding graphs and figures are provided in below. These graphs also confirm the above-mentioned insights.
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Table 8: The top twenty scenarios with the lowest Training MSE

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Table 9: The top twenty scenarios with the lowest Validation MSE
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<td>Weight Type</td>
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<td>Number of negative errors(output-target)</td>
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<td>Offset of Regression</td>
<td>Train Performance</td>
<td>Validation Performance</td>
<td>Test Performance</td>
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### Table 10: The top twenty scenarios with the lowest Test MSE

<table>
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<tr>
<th>Scenario</th>
<th>Transform function</th>
<th>Output Type</th>
<th>Weight Type</th>
<th>Number of neuron</th>
<th>Number of positive errors(output-target)</th>
<th>Number of negative errors(output-target)</th>
<th>Regression fit</th>
<th>Offset of Regression</th>
<th>Train Performance</th>
<th>Validation Performance</th>
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<td>0.825</td>
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</tbody>
</table>
Figure 14: Samples of generated graphs; top left and bottom: Selected feature-X1 X2 X3 X4 X6 X7 X10-ChangedWeight—Y2—10—logsig for low test MSE; top right and bottom right: Selected feature-X1 X3 X4 X6 X8 - ChangedWeight-Y2-10-logsig for low validation MSE;

The summary of all the previous insights are provided table 11 below. Contemplating all the provided insights in below, ANN models with the following features are likely to have high performance measures (e.g., low positive and negative, MSE errors): X1 (Age), X2 (Gender), X3 (Week day of Arrival), X4 (Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category).
<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>Insights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest number of positive and negative errors (output-target): Tables 4-5</td>
<td>ANN models that include X1 (Age), X2 (Gender), X4 (Date and Time of Arrival), X5 (Mode of Arrival) and X6 (Triage Category) result in a lower number of over-prediction as well as under-prediction errors.</td>
</tr>
<tr>
<td>ANN models that perform well when their predictions are tested/validated against actual data: Table 6</td>
<td>“purline” as neuron transfer function</td>
</tr>
<tr>
<td>ANN models and scenarios with a low MSE error: Tables 7-9</td>
<td>“Logsig” transform function.</td>
</tr>
</tbody>
</table>

Table 11: Summary of found insights.

In sum, in this chapter, not only describes the neural network models in details, but also, those models’ application for healthcare services are illustrated. In particular, the results of a computationally intense meta-algorithm indicate that some healthcare factors have more significant effects on waiting time in ED.
Chapter 6
Discussion, Conclusion and, Future Work
CHAPTER 6 – DISCUSSION, CONCLUSION AND FUTURE WORK

6. Discussion, Conclusion and, Future Work

In summary, according to the discussions in this chapter, the newest definition of quality is the “degree to which a set of inherent characteristics fulfils requirements” (ISO 2005). Moreover, as stated by the International quality Standard, all organizations are encouraged to adopt a process approach for their quality management systems. In this perspective, quality control process should interact with other organizational processes.

6.1. Healthcare Service Quality Analysis and Neural Network Models

According to the definition of quality ” (ISO 2005), to achieve an acceptable quality level, all needs and expectations should be considered. Moreover, since 2000, and according to ISO 9001:2015 standard, quality management with process approach has been motivated. In that process approach, quality control is an organizational process that should interact with other quality and organizational processes in order to enable organization to implement its quality objectives and goals.

As services, despite products, cannot be evaluated using tangible measures (e.g., durability defects (Crosby Philip B. 1979; Garvin David A. 1983)), definition of service quality is rather an abstract and elusive concept. Consequently, different subjective models (e.g., SERVQUAL) for service quality have been developed.
Service quality measurement becomes more challenging when it needs to be conducted in the context of healthcare. As discussed in the previous chapters, different factors such as the distributed structure of healthcare industry are drivers of high complexity in healthcare service quality measurements. Thus, more sophisticated tools are required to cope with the highly complicated task of healthcare service quality measurement.

One of the tools that has been applied for quality control is neural network model. This model, especially, has been used for both univariate and multivariate quality control processes: (Zorriassatine F. and Tannock J.D.T. 1998), (Pugh G. A. 1989), (Amiri Amir hossein, Maleki Mohammad Reza et al. 2014), (M.R. Maleki, A. Amiril et al. 2012), (Mojtaba Salehi, Reza Baradaran Kazemzadeh et al. 2012), (MR Maleki and Amiri 2015). In addition, it has been incorporated for both uni-attribute and multi-attribute non-measurable quality characteristics (Su C. T. and Tong L. I. 1997), (M.R. Maleki, A. Amiril et al. 2012), (Amiri Amir hossein, Maleki Mohammad Reza et al. 2014).

Application of neural network models have not been limited to only manufacturing context, and service quality initiatives in diverse service sectors (e.g., banks, restaurants) have been investigated by those models (Ravi S. Behara, Warren W. Fisher et al. 2002), (Mahapatra and 2006), (Concepción Garrido, Rocío de Oña et al. 2014), (Aisyah Larasatia, Camille DeYongb et al. 2012), (S.S. Mahapatra and Khan 2007), (Anand Prakash, R.P. Mohanty et al. 2011), (Chang-long 2009), (Mir Fakhroddini, Taheri Demne et al. 2010). In a more narrower area, healthcare service quality context, only two papers have applied neural network models (Anand Prakash and Mohanty 2012).
6.2. Theoretical and Practical Implications

6.2.1. Theoretical Insights

Variability and unpredictability are typical characteristics for emergency departments. Especially, the amount of demand at each time (i.e., patients’ arrival) is uncertain. In addition, patients who arrive at ED can have diverse clinical conditions (e.g., age, health issue severity), and consequently, not only demand is uncertain, but also, it is diverse. For instance, there are urgent and non-urgent patients at EDs of the hospitals.

In addition to the aforementioned features, there are different types of resources like nurses and physicians, and their availability can be also uncertain, and prone to unknown changes. Moreover, those resources like physicians can be of different types and classes, depending on their skills and experiences. Similarly, different groups of nurses with different features (e.g., gender, qualifications) operate at ED, and their scheduling and planning can be a highly challenging and complex task.

According to the above discussed features of ED in the hospital, an ED can be considered as complex system. In such systems, decision-makers (e.g., ED managers) need to understand and capture the complex relationships among the influential variables on service quality measures like length of stay.

In order to understand the relationships among the influential variables of service quality in ED, different types of models can be applied. One type of models includes those that assume a linear relationship among those decision variables and the service quality
model. For instance, linear regression models might be used to analyze association of different variables on service quality (i.e., say length of stay) at ED. However, those models are prone to several issues. On the one hand, linear models can rarely exist among variables, and also those models might lead to poor fit of non-normal output variables (M.Xu, et al. 2013), (M. Qualls, D.J. Pallin, J.D. Schuur (2010). On the other hand, using linear regression to model patient arrivals may result in a phenomenon that is called multicollinearity, where input variables are correlated (M.Xu, et al. 2013).

In addition to linear regression models to analyze ED service performance measures (e.g., LoS), other approaches have also been taken. For example, patients could be grouped according to their similar characteristics to reduce the complexity and uncertainty in the ED management, and consequently, improve the quality of provided services to the ED patients (M.Xu, et al. 2014). Three common approaches for patients grouping are as follows: (i) Casemix conducts patient grouping based on diagnosis-related grouping, (ii) Length of stay (LoS) is another proxy measure of resource consumption in EDs, (iii) Patient pathway grouping clusters patients according to their physical movements within a healthcare facility (ibid).

In contrast to these models, my approach toward service quality improvement in ED has been focused on using ANN models. ANN models are nonlinear models for which the previously discussed shortcomings of linear and clustering approaches do not hold. Furthermore, with a neural network, it is possible for the ANN model to learn from its environment, and to improve its performance through learning.
ANN models have other critical features that make them more suitable for prediction and analysis of service quality measure in EDs. On the one hand, since majority of service quality characteristics are attribute ones, and given that, ANN models have no restrictions the number and type of inputs (e.g., attribute, variable), therefore, their usage for analysis of service quality in EDs poses no significant challenges. More importantly, ANN models assume no assumption on statistical distribution of variables and their dependency, and their implementation for healthcare service quality does not need some data preprocessing tasks.

Since one of the challenges of ANN models is overfitting, and also, these models performance depends on input variables, I elaborate on applying ANN models in a particular way. In fact, in the illustrated case study in Chapter 4, there were 24 different independent variables (e.g., as time of arrival, age of patients) that were perceived to be influential variables on patients waiting time in ED. However, as there were no concrete reasons for ED stakeholders (e.g., managers, decision-makers), I need to elaborate on ANN models.

The used meta-algorithm has been designed such that, at each iteration, a subset of independent variables (e.g., as time of arrival, age of patients) are selected according to desired features (e.g., number of independent variables). Then, and in the next step, ANN models for that scenario (i.e., selected subset of independent variables) is built, performance the built ANN models are evaluated and recorded. These steps are repeated for a large number of times until all required iterations are conducted.
The developed meta-algorithm and ANN models have two general and theoretical implications for use of data analytics in healthcare system (Hian Chye Koh and Gerald Tan 2005). On the one hand, these models can enhance ED management systems by identification of those highly influential ED features on patients waiting time. That identification can enable healthcare managers to cope with essential complexity and challenges of ED systems with more appropriate resource allocation and resource usage tracking.

The importance of such enhancement of EDs in coping with ED complexity and uncertainty can be highlighted by considering the following facts (Melissa L. et al. 2008). What is known as ED crowding occurs when patients demand for services exceeds ED’s available capacity. Relevantly, in the United States during 1995 and 2005, the annual number of ED visits is escalated from 97 million to 115 million (about 20%). Despite that fact, however, the number of hospital EDs nationwide declined by 9%.3 (ibid). Consequently, with such increased demand and dropped supply, ED systems are expected to be crowded. In such situations, similar models to the one presented in this thesis can be deployed to improve quality of provided service by improving resource allocation and scheduling.

On the other hand, the presented model and algorithm in this thesis can be considered in line with policies and approaches toward improving customer relationship management (CRM). Generally, CRM focuses on interactions of organization with its customers, and in the healthcare context, EDs need to determine patients’ usage pattern in order to improve their patient satisfaction level. Relatedly, according to my results of deploying
the developed model and algorithm for the case-study, reveal that patients’ time and mode of arrival are critical variables (that has been observed in other studies (M.Xu, et al. 2013). Thus, in order to improve patients’ service satisfaction, ED managers need to consider those variables.

6.2.2. Implications for Practice

The ANN model and meta-algorithm can be implemented in practice with other relevant data mining and Healthcare-related Information Systems in hospitals. In particular, the presented meta-algorithm can be implemented as a waiting time prediction Decision Support System (DSS) which is integrated with other healthcare information systems. Such properly integrated DSS for waiting time prediction along with other systems in EDs are likely to enable ED managers to analyze their ED system and enhance their system efficiency and effectiveness in a timely manner.

The following discussions illustrate how waiting time DSS can be integrated with other ED information systems. Workflow management software that include patients’ arrival and other background information can be an information source for waiting time DSS. That can be implemented by having a common database for both information systems, or linking their databases. Moreover, resource and capacity management information systems can be also linked with waiting time DSS. Especially, the former systems can use the past results of waiting DSS in order to analyze expected performance of system under different resource and capacity allocation scenarios. Furthermore, the waiting time
predication system can use the past transaction and records on resource management software to run its model, and update waiting time predictions.

Waiting time predication DSS can also use the recorded data in other information systems where patients care path and their treatment urgency along other relevant data are recorded. For instance, often, after triage, patients join a queue to get a bed, after which he will be receiving some treatment procedures. Moreover, a patient within the treatment process may undergo different treatment processes and might exist at different end points in EDs (e.g., exit ED and hospital, enter inpatient ward). All these steps can be recorded in relevant information systems, and then be used as inputs for waiting time predictions in future.

6.3. Answering the Research Questions

In this section the three key research questions are answered as below.

1) How can we combine some high level and complex concepts like neural network as an objective model in order to evaluate and monitor service quality instead of current subjective methods? The outputs that are presented in this thesis indicate that ANN models can be an effective means by which service quality in ED can be measured and evaluated. Particularly, these models impose no restriction on the type of quality measures/variables, and that makes them highly useful for healthcare service quality management for which usually, different variable types might be necessary. Furthermore, associations among variables are also without restriction in
ANN models, and hence, they are expected to have higher chances in capturing complex relationships among healthcare service measures.

2) Why might be feasible to replace current subjective models by neural network model? In this thesis, some potentials of using ANN models for healthcare service quality management are illustrated, and as discussed, these models can be implemented as Decision Support Systems which is linked with the other IT systems in hospitals. However, I expect other unseen potential of ANN models for healthcare services that might need further attention and investigation. Such investigations are likely to reveal more in detail how these models can be used instead of subjective models.

3) If there is any probable error in network model, what is the source of error? How the error can be eliminated by investigating error sources? As discussed in this thesis, ANN models like any other models are prone to difference overfitting and under-estimation errors. Moreover, there can be model implementation errors where ANN model ingredients are mis-specified (e.g., including or excluding less relevant quality measure, number of layers in the ANN model). In order to manage those latter errors, I elaborated and presented a meta-algorithm that searches for the best ANN scenarios (with low errors), and hence it can be useful in managing such likely errors.
6.4. Limitations and Future Research

Similar to any research endeavor, there are some limitations on this thesis and its model and results. One of such limitations is use of model on only one ED case study. Specially, the results of deploying model for more than one hospital not only improve confidence on applicability of model, but also, are likely to reveal some other hidden insights. Other limitations of this study involve only aggregated data about ED process. That is, there were only data on the overall ED process, and no data about ED sub processes. Finally, it is noted that this research focused on the Australian Healthcare context. To expand this and generalize the findings to other healthcare contexts e.g., in US it will be necessary to ensure that appropriate nuances of these systems including payment structures are also taken into account to ensure that a meaningful and useful result ensues.

There are several avenues for future research. First of all, the presented model and algorithm can be extended and improved on several directions. One important aspect of these models is selection of input variables. That is which independent variables should be incorporated into the ANN model. In this thesis, that task is conducted by interacting over different subsets provided by the users. In machine learning field, this task is feature selection that is known in machine learning applications as part of the pre-processing step where a number of features minimal predictive information are eliminated (Hinton et al. 2006; Vieira et al. 2010); however, as future research opportunities, this thesis approach might be improved using the following methods: Particle Swarm Optimization (S.

In addition, the applied ANN model in this thesis can be enhanced by considering Deep Neural Network (DNN) models. In particular, researches in machine learning field demonstrate that the models with greater depth attain significantly improved forecast performance in most machine learning applications (Goodfellow, Bulatov, Ibarz, Arnoud, & Shet, 2013; Kahou et al., 2013; Szegedy et al., 2015). Thus, analysis of ED waiting time prediction by DNN models, and their comparison with ANN models can be another future research opportunity.
References
References


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Koey Sehwail and Camille De Yong (2003), Six Sigma in Health Care, International Journal of Health care Quality Assurance incorporating leadership with health services 16,4.

M. Qualls, D.J. Pallin, J.D. Schuur (2010), Parametric versus nonparametric statistical tests: the length of stay example, Academic Emergency Medicine, 17, pp. 1113-1121


M. Xu, T.C.Wong, K.S.Chin (2013), Modeling daily patient arrivals at Emergency Department and quantifying the relative importance of contributing variables using artificial neural network, Decision Support Systems Volume 54, Issue 3 Pages 1488-1498


Melissa L. McCarthy, Scott L. Zeger ,Ru Ding MS, Dominik Aronsky Nathan R. , Gabor D. Kelen MD (2008), The Challenge of Predicting Demand for Emergency Department Services, Academic Emergency Medicine, Volume 15, Issue 4, Pages 337–346


Niavarani M. T. (2014). Multi-variate attribute quality control (MVAQC), School of Mechanical Engineering, The University of Melbourne. PhD.


Ross McL Wilson, Bernadette T Harrison, Robert W Gibberd and John D Hamilton (1999), An analysis of the causes of adverse events from the Quality in Australian Health Care Study, MJA 1999; 170: 411-415


Simon Haykin. (1999). Neural Networks and Learning Machines, 3rd Ed., McMaster University Hamilton, Ontario, Canad


Thongsamak Sasima (2001). Service Quality: Its measurement and Relationship with Customer Satisfaction, Virginia Tech College of Engineering, USA


Trevor Hastie, Robert Tibshirani, Jerome Friedman (2001), The Elements of Statistical Learning, Data Mining, Inference, and Prediction, second Ed., Springer


Appendices

• Appendix A: SQL Commands, used for Data Preparation

• Appendix B: Paper published from this research

• Appendix C: Book Chapter published from this research (Lean Thinking for Healthcare (Springer 2013))

• Appendix D: Student’s another PhD Thesis – The university of Melbourne (2014)
Appendix A: SQL Commands, used for Data Preparation

```sql
select distinct t3.[Waiting Time ]
  ,t3.[Deviation of waiting time]
  ,t3.[Age]
  ,t3.[Gender]
  ,t3.[Weekday]
  ,t3.[Arrived Dttm]
  ,t3.[Arrival Mode]
  ,t3.[Triage]
  ,t3.[Provisional Diagnosis]
  ,t3.[Diagnosis Category]
  ,t3.[ED Occupancy-Beds]
  ,t3.[%ED Bed Occupancy]
  ,t3.[Patients Awaiting Bed or ED Admit]
  ,t3.[%Awaiting Bed ]
  ,t3.[Arrivals in Hr Prior]
  ,t3.[Seen Dttm]
  ,t3.[Seen per hour]
  ,t3.[Departed Dttm]
  ,t3.[Departures in HR Prior]
  ,t3.[Admitted]
  ,t3.[Dr Hr]
  ,t3.[Nursing Hr]
  ,t3.[Clerical Hours]
  ,t3.[%dr last hr shift]
  ,t3.[Is ICU admission?]}
  ,t3.[Hospital Occupancy]
  ,t3.[Column 26]
 ,t2.row,  
  t3.[Provisional Diagnosis] from
  [WindowsKinect1].[dbo].[Summary V4] as t3 inner join (select
  ROW_NUMBER() over (Order by [Provisional Diagnosis]) as row,*
  from (select distinct [Provisional Diagnosis]
  from [WindowsKinect1].[dbo].[Summary V4]) as t1
  where t1.[Provisional Diagnosis]<>'' AND t1.[Provisional
  Diagnosis]<>'X7') as t2  on t2.
  [Provisional Diagnosis]=t3.[Provisional Diagnosis] order by t3.[Arrived Dttm]

select distinct t3.[Waiting Time ]
  ,t3.[Deviation of waiting time]
  ,t3.[Age]
  ,t3.[Gender]
  ,t3.[Weekday]
  ,t3.[Arrived Dttm]
  ,t3.[Arrival Mode]
  ,t3.[Triage]
  ,t3.[Provisional Diagnosis]
  ,t3.[Diagnosis Category]
```

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t3.[ED Occupancy-Beds],
t3.[%ED Bed Occupancy],
t3.[Patients Awaiting Bed or ED Admit],
t3.[%Awaiting Bed ],
t3.[Arrivals in Hr Prior],
t3.[Seen Dttm],
t3.[Seen per hour],
t3.[Departed Dttm],
t3.[Departures in HR Prior],
t3.[Admitted],
t3.[Dr Hr],
t3.[Nursing Hr],
t3.[Clerical Hours],
t3.[%dr last hr shift],
t3.[Is ICU admission?],
t3.[Hospital Occupancy],
t3.[Column 26],
t2.row,
t3.[Diagnosis Category] from [Windows_Kinect1].[dbo].[Summary V4] as t3 inner join (select ROW_NUMBER() over (Order by [Diagnosis Category]) as row,* from (select distinct [Diagnosis Category] from [Windows_Kinect1].[dbo].[Summary V4]) as t1 where t1.[Diagnosis Category]<>'' AND t1.[Diagnosis Category]<>'X7 (seperated)') as t2 on t2.[Diagnosis Category]=t3.[Diagnosis Category] order by t3.[Arrived Dttm]
Appendix B: Paper published from this research

The Suitability of Artificial Neural Networks in Service Quality Control and Forecasting for Healthcare Contexts

Research-in-Progress

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ABSTRACT
Over the last decade there has been considerable research into the area of service quality. Service, however, as an intangible, perishable, and heterogenic transaction, is very difficult to quantify and measure, and little success has been reported on a systematic approach in modeling of quality of service transactions (with SERVQUAL and its derivatives as the notable exception). In this paper, we propose an Artificial Neural Network (ANN) to monitor quality of service transaction as a dynamic and real-time monitoring and forecasting system. ANNs are widely used in many engineering fields to model and simulate complex systems. The resulting near-perfect models are particularly suited for applications where real-world complexities make it difficult or even impossible to mathematically model the system. Given the complex nature of healthcare decisions, the following reports on a research in progress study that focuses on applying ANN to a specific healthcare context of the emergency room.

Keywords
Service, Service Quality, Artificial Neural Network, ANN, Healthcare, emergency room, emergency department

INTRODUCTION
The service sector in developed countries such as the United States and Australia currently accounts for some 80 per cent of all economic activity (DPAT 2008; Spohrer et al., 2007). The service economy encompasses not only private enterprise but also the diverse services provided by government, such as education and healthcare. Service systems can be described as dynamic configurations of resources (people, technologies, organizations and shared information) that can create and deliver value to customers, providers and other stakeholders (IBM and IBM, 2008: p.18).
Despite the sheer size of economic activities that are classified as services, service quality remains an abstract and elusive construct mainly because of three unique features: intangibility, heterogeneity, and inseparability of production and consumption of services (Parasuraman A., Valarie A. Zeithaml et al. 1985). There is not even global consensus on what constitute quality in service transactions; there are indeed a number of definitions for quality. One of the most comprehensive definitions of quality is the "degree to which a set of inherent characteristics fulfills requirements" (ISO 2005). In this definition, requirements is defined as the "need or expectation that is stated, generally implied or obligatory" (ISO 2005). This definition of quality is different than that defined in manufacturing, for example, where definition of the requirements and hence the quality is set and measured objectively by such indicators as durability and number of defects (Crosby Philip B. 1979; Garvin David A. 1983). In the absence of objective measures, subjective methods such as SERVQUAL (Parasuraman A., Valarie A. Zeithaml et al. 1988), SERVRPERF (Cronin J. J. and Taylor S. A. 1992), Qualitometer (Franceschini F., Cignetti M. et al. 1988) have been developed and used extensively in service sector.

Computational techniques and simulation methodologies have played a significant role in modeling and optimization of production and process management over the past few decades. Lack of objective measures in services however, has hindered adoption of simulation, control, and computational techniques in this section of the economy. There is now a clear and growing understanding amongst service scientists that there is a need for a modeling or simulation tool for services.

Artificial neural networks (ANNs) are computational networks that attempt to crudely mimic the networks of neurons of biological system such as that of humans or animals (Daniel Graupe 2007). ANNs belong to a category of meta-heuristic modeling, control, and optimization algorithms, called Evolutionary Algorithms (EAs). EAs are inspired by nature through exhibiting complex collective behavior from a collection of seemingly simple agents. These include artificial neural networks, genetic algorithm, tabu search, ant colony optimization, and simulated annealing. Most of these techniques have long been used in engineering and in industry; there are reports of the application of ANNs for example, in quality control (Abbaee Babak 2007). Their application in quality control however, has been mostly limited to manufacturing industry. We propose there is merit in considering EAs in service quality control and service quality forecasting.

In the following section we cover service quality as it has been studied in academia, followed by an introduction to ANNs. We conclude this paper by summarizing advantage and disadvantage of using ANNs in service quality control and service quality forecasting as well as a case study in healthcare industry.

SERVICE QUALITY

The concept of service quality as a whole construct is large and varied. The conceptual foundation for service quality was emerged from the works of a handful of researchers who examined the meaning of service quality (Sasser W. W., Olsen R. P. et al. 1978; Gronroos Christian 1982).

Service quality is usually expressed from customer point of view as a function of customer’s expectations of the service compared to the perception of the actual service experience (Gronroos Christian 1984; Parasuraman A., Valarie A. Zeithaml et al. 1985; Johnston R. and Heineke J. 1998). Imrie et al (Imrie B. C., Cadogan J. W. et al. 2002) showed that using service quality as a key point of market differentiation positively influenced customer retention and market growth. Interestingly, Parasuraman et al (Parasuraman A., Valarie A. Zeithaml et al. 1988) stated that in measuring perceived service quality, the level of comparison is what a customer should expect, whereas Mahdavinia (Mahdavinia H. 2007) prefers in measuring customer satisfaction, the appropriate comparison is what a customer would expect. In addition, service levels need to be set and strategies devised that first recognize the relative impact of individual factors on overall perceptions and secondly, link them to organization’s quality strategy (Johnston R. and Heineke J. 1998).

Overall there have been five predominant service quality measurement tools reported in literature since 1991. These tools can be summarized in chronological order in table 1:
<table>
<thead>
<tr>
<th>Tool</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SERVQUAL</td>
<td>SERVQUAL is used to measure consumer's and service providers' expectations and perceptions. This approach enables the exceptions and perceptions gap to be assessed, while providing a measure of service quality gap and service delivery gap. According to Parasuraman et al model (Parasuraman A., Valarie A. Zeithaml et al. 1988), the gap between consumer's expectations and perceptions are a function of several other gaps in the service delivery process (Mangold G. and Emin B. 1991). Some other models were proposed after the first introduction of SERVQUAL.</td>
</tr>
<tr>
<td>Qualiometro</td>
<td>Qualiometro (Franceschini F., Cignetti M. et al. 1988) is founded on the determinants of service quality. Customer expectations and perceptions are evaluated in two distinct moments. Quality evaluation is carried out by means of a comparison between quality and expectations and perception profile. Qualiometro employs the same semantic scale and dimensions as SERVQUAL (Mahdavinia H. 2007).</td>
</tr>
<tr>
<td>Two-way</td>
<td>Two-way used latent evaluations factors based on the theory that service quality is evaluated by answers given by customers about “objective” (quality attribute) and “subjective” (satisfaction level) (Schwaneveldt S. and Endkawa T. 1991; Mahdavinia H. 2007)</td>
</tr>
<tr>
<td>SERVPREF</td>
<td>Cronin et al (Cronin J. J., and Taylor S. A. 1992) proposed SERVPREF based on their survey on theory that service quality is evaluated by perception only. The key difference with SERVQUAL is that only perceptions is evaluated (Mahdavinia H. 2007).</td>
</tr>
<tr>
<td>Normed quality</td>
<td>Normed quality (Tras K. K. 1994) is uses the distinction between ideal expectation and feasible expectation to calculate service quality. It also employs the same semantic scale and dimensions as SERVQUAL. Normed is the second well-known model (after SERVREF) that is derived from SERVQUAL (Ghosheiri K. and Pishdadi S. 2006)</td>
</tr>
</tbody>
</table>

Table 1 The Five Major Service Quality Measurement Tools


All the above service quality models share a common feature; they evaluate quality of services through the same approach; they apply questionnaire or other data gathering tools and evaluate the quality based on their respective subjective concepts.

Many quality characteristics can be measured and stated as a numerical value. For instance, service delivery may be timed and reported in seconds or minutes or hours. These types of quality characteristics are called “variable characteristics”. Advantage of questionnaire-based approaches is in their ease of collecting and the use of variable characteristics. There are however, other types of measurements that can only assume nominal (reject, accept), ordinal (bad, good, excellent), or categorical (married, single, divorced) values. These are called “attribute characteristics”. Collecting and processing of attribute characteristics are a much harder proposition as they inherit subjective principal and values. We propose the use of Artificial Neural Networks (ANNs) in order to overcome the complexity in processing these tacitly implied and subjective measurements. ANNs have been used in engineering and manufacturing, to the best of the author’s knowledge they have not been applied in service quality control and forecasting.
Artificial Neural Network

Artificial Neural Networks (ANNs) mimic biological neural networks to model and solve a variety of problems arising in forecasting, function approximation, pattern classification, clustering, and categorization (Pao Y.H. 1989). There are different classes of network architectures including single-layer feed-forward networks, multi-layer feed-forward networks, and recurrent networks (Simon Haykin 1999), but figure 1 shows a basic concept of a nonlinear ANN model.

Figure 1 — nonlinear model of neuron

After constructing a neural network, it needs to be trained based on some available data (different inputs and their corresponding outputs) to be able to forecast the output for future inputs with an acceptable error level through an ongoing modification process. The property that is of primary significance for a neural network is the ability of the network to learn from its environment, and to improve its performance through learning. Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by manner in which the parameter changes take place. There are different types of learning including unsupervised learning and supervised learning. In the supervised training process, the user plays an important role as the network learns. However, in an unsupervised process the user lets the network train itself (Simon Haykin 1999).

Merits and demerits

Generally, the use of neural networks offers useful properties and capabilities including but not limited to: (Simon Haykin 1999)

- **Nonlinearity.** It can be linear or nonlinear.

- **Input-Output Mapping.** The synaptic weights (free parameters) of the network modified to minimize the difference between the desired response and the actual response of the network produced by the input signal in accordance with an appropriate statistical criterion.

- **Adaptivity.** It has a built-in capability to adapt their synaptic weight to changes in the surrounding environment.

- **Uniformity of Analysis and Design.** Basically, neural network enjoy universality as information processors.
• **Neurobiological Analogy.** The design of a neural network is motivated by analogy with the brain, which is a living proof that fault tolerant parallel processing is not only physically possible but also fast and powerful.

Regardless of all aforementioned merits, neural network has the following drawbacks (Jerome Friedman, Trevor Hastie et al. 2001):

- Trial and error element to building good models (In training phase)
- It is hard to interpret what is happening in the model (Black Box) and people only see the inputs and outputs
- Model performance relates to starting input values and parameters.

### Application of Artificial Neural Network to Service Quality

In spite of considerable number of available service quality methods, there are some shortcomings shared between them:

1. Firstly, all proposed methods for quality control in service industry are somehow subjective and they are mostly designed based on SERVQUAL. These models employ static methods for data analysis. A periodical analysis can be performed in a regular base (e.g., monthly, 6 monthly, yearly and etc) if trends are to be determined. These methods are retrospect and are not able to monitor service quality in real-time. Whereas, in dynamic methods, one can monitor quality of delivered service in real-time (as the service is being delivered). Based on the past history (training data set), and real-time data gathering, artificial neural networks have the ability to forecast the outcome (service quality). Exactly as humans deal with imprecise data, service quality forecasting can be performed even in the case of imprecise or imperfect real-time data.

2. Secondly, in subjective methods, the correlation between different factors is not reckoned and each characteristic (e.g., reliability, responsiveness and etc.) is monitored through one or more questions in the questionnaire. However, in reality characteristics and attributes of service transactions do correlate and can affect service quality indirectly. Considering these characteristics in isolation ignores such indirect consequences.

3. Thirdly, in applying subjective model based on questionnaire or other means of data gathering, some variable data are missed or converted to numeric attribute. For instance, qualitative values are usually given numeric rankings. Artificial neural networks can deal with qualitative values as they are, alleviating this limitation.

Based on the above, it seems the use of ANNs for service quality control and service quality forecasting is well justified. A model for applying ANNs in service quality control is proposed in Table 2.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem</td>
<td><strong>Definition</strong> Case description, problem assumptions (service quality model ...)</td>
</tr>
<tr>
<td>Designing</td>
<td><strong>Type of model</strong>, <strong>type of connections</strong>, <strong>number of layers</strong>, <strong>number of neurons</strong>, <strong>activation function</strong>, <strong>cutting value</strong></td>
</tr>
<tr>
<td></td>
<td>Estimating parameters (Based on historical data)</td>
</tr>
<tr>
<td></td>
<td>Generating training data based on estimated parameters</td>
</tr>
<tr>
<td>Training</td>
<td>Training of neural network</td>
</tr>
<tr>
<td>Verification</td>
<td>Testing trained network based on random generated or historical data</td>
</tr>
<tr>
<td>Programming</td>
<td>Coding and running the network based on related assumption (cutting value and ...)</td>
</tr>
<tr>
<td>Validation</td>
<td>Validation of network in real case study</td>
</tr>
</tbody>
</table>

*Table 2 — A model for applying ANN in service quality*
Application to Healthcare context

There are some different services that can be nominated in application case study e.g. education, public transportation, banking, healthcare, and so forth. In comparison with other types of servicing, healthcare providers face many challenges, while they are concurrently under public scrutiny as consumer demands escalate. Medical care quality control and improvement as confidence in the medical community providing safe and effective patient care. Note that poor quality in patient care processes can run the spectrum from minor dietary issues to patient morbidity and fatality. It seems that applying a biological-origin concept in health care industry would be interesting. (Gimmy W. Frings and Laura Grant 2005). Health care is the most crucial service industry because of its nature of zero tolerance for mistakes and potential for reducing medical (Y.H. Kwak and Aabari 2006). Health care is the largest service industry accounting for 17 percent of the US GDP ahead of education at 10 percent (Richard C. Larson 2009). There are about 7,500 hospitals in the United States but about 4,000 institutions of higher education (Richard C. Larson 2010).

The Commonwealth Fund, in its annual survey, “Mirror, Mirror on the Wall”, compares the performance of the health care systems in Australia, New Zealand, the United Kingdom, Germany, Canada and the U.S. The Organization for Economic Co-operation and Development (OECD) also collects comparative statistics, and has published brief country profiles (The Commonwealth Fund 2007; Organization for Economic Co-operation and Development 2008; Wikipedia 2010).

The Institute of Medicine’s definition of quality has proved of enduring usefulness: “Quality is the extent to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge” (Mark R. Chassin 1998).

Some operational inefficiencies are associated with the direct medical service delivery process. Others are associated with the administrative, logistical, and operational side of the healthcare delivery system. Both areas can benefit from systematic process innovation activities (Henk de Koning, John P. S. Verwer et al. 2006).

A lot of different attribute and variable quality characteristics can be considered in healthcare to monitor predict and improve. (Loey Sehwail and Camille De Yong 2003; Richard Stahl R, Schultz B et al. 2003) posit that the quality characteristics in health care can be classified into four categories:

- Service level (e.g. access to care, wait time, service time);
- Service cost (e.g. cost per unit of service, labor productivity);
- Customer satisfaction (e.g. patient or family, referring physician, employee);
- Clinical excellence (e.g. guidelines for medication or treatment, standard procedures for patient monitoring)

From different angle, Elizabeth A. McGlynn et al. (Elizabeth A. McGlynn, Steven M. Asch et al. 2003) proposed different quality indicator in three types of care including preventive, acute and chronic and in four different functions including screening, diagnosis, treatment and follow up. In an analytical paper published by The Quality in Australian Health Care Study (QAHCIS), Ross McL. Wilson et al. analyzed the cause of adverse events resulting from health care in Australia from different categories like human error categories, delay categories, treatment categories, and investigation categories(Ross McL Wilson, Bernadette T Harrison et al. 1999).

A case study in Healthcare

In order to check the application of ANN in service quality control and forecasting in healthcare industry. A case study is under progress in emergency department of one of the biggest hospitals in Melbourne, Australia. This emergency department primarily serves an adult population and has a yearly attendance of over 28000 patients with 10000 admissions to hospital. We have chosen such an approach since as noted by Yin (1994, 2003) an exemplar case study is a very appropriate methodology when conducting such exploratory and theory building research. In addition we subscribe to rigorous qualitative techniques as outlined by Kvale(2008), Boyatzis(1998) and Yin(2009) regarding conducting of rigorous qualitative research and construction of appropriate themes for thematic analysis.

In this study, the output of the network is considered “waiting time to see a doctor” with the purpose of finding the most critical input factors on waiting time to decrease that and consequently improve customer (patient) satisfaction as well as forecasting the patient’s waiting time in future based on the ANN model. The primary model parameters are shown in table 3.
Discussion and Concluding Remarks

Service quality and methodologies of measuring it were discussed and then from the case vignette contextualized for a healthcare context. In this way we demonstrated the potential benefits of applying ANN into healthcare to facilitate the achievement of superior healthcare delivery. The gaps in the currently available methodologies were highlighted. Based on the lessons learnt in manufacturing in dealing with analogous problems, the use of Evolutionary Algorithms (EA) in service quality control and forecasting are proposed, and a simple model for applying artificial neural networks (a sub-class of EA) is presented.

For completeness, it is noted that the application of artificial neural networks in service quality control and forecasting have the following characteristics:

1. No restriction on the type of inputs and outputs (qualitative values, quantitative attributes, or any combination thereof)
2. No assumption is made on the statistical distribution of variables and their interdependence
3. No limitation on the number of inputs and outputs (although it is noted that as the number of inputs and outputs increase, the network might become prohibitively complex).
4. No requirements on access to large data sets. EV can be trained and used with much smaller data sets than statistical methods afford.
5. Computationally very efficient, which can translate into much faster data analysis; affording near real-time data analysis in the case of artificial neural networks.

We believe artificial neural networks are a prime candidate in service quality control and service quality forecasting. Research is already underway in designing and applying an artificial neural network as a dynamic model for monitoring and forecasting of service quality in the healthcare industry. It is a research in progress and at present which is in modeling phase. The model parameters have already been determined and the data gathering is in place simultaneously. In next step, the designed model is trained, verified and validated using the historical and fresh data.
<table>
<thead>
<tr>
<th>Model parameters</th>
<th>Measure</th>
<th>Description</th>
<th>Type of Measure (attribute/variable)</th>
<th>Importance Weight (1-5)</th>
<th>Operational Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>Y</td>
<td>Waiting Time</td>
<td>variable</td>
<td></td>
<td>0-480 minutes</td>
</tr>
<tr>
<td></td>
<td>X1</td>
<td>Age</td>
<td>variable</td>
<td>3</td>
<td>0-110</td>
</tr>
<tr>
<td></td>
<td>X2</td>
<td>Gender</td>
<td>attribute</td>
<td>1</td>
<td>M/F</td>
</tr>
<tr>
<td></td>
<td>X3</td>
<td>Time of Arrival</td>
<td>variable</td>
<td>4</td>
<td>00:00-24:00</td>
</tr>
<tr>
<td></td>
<td>X4</td>
<td>Day of Arrival</td>
<td>attribute</td>
<td>4</td>
<td>Mon-Sun</td>
</tr>
<tr>
<td></td>
<td>X5</td>
<td>Mode of Arrival</td>
<td>attribute</td>
<td>3</td>
<td>Ambulance vs walk-in</td>
</tr>
<tr>
<td></td>
<td>X6</td>
<td>Acuity</td>
<td>attribute</td>
<td>4</td>
<td>1,2,3,4,5</td>
</tr>
<tr>
<td></td>
<td>X7</td>
<td>Presenting Complaint</td>
<td>attribute</td>
<td>2</td>
<td>Gastrointestinal/Respiratory/Cardiovascular/Neurological/Eye/Ear/Injury-minor/Injury-Major/psychiatry/gender/primary/skin/general/musculoskeletal</td>
</tr>
<tr>
<td></td>
<td>X8</td>
<td>ED Occupancy</td>
<td>variable</td>
<td>4</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X9</td>
<td>Hospital Occupancy</td>
<td>variable</td>
<td>4</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X10</td>
<td>% ED occupancy patients waiting for beds</td>
<td>variable</td>
<td>4</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X11</td>
<td>Arrivals per Hour</td>
<td>variable</td>
<td>4</td>
<td>0-20</td>
</tr>
<tr>
<td></td>
<td>X12</td>
<td>Discharges Per Hour</td>
<td>variable</td>
<td>3</td>
<td>0-20</td>
</tr>
<tr>
<td></td>
<td>X13</td>
<td>Medical Staffing (hourly)</td>
<td>variable</td>
<td>5</td>
<td>2 to 15</td>
</tr>
<tr>
<td></td>
<td>X14</td>
<td>Medical Staffing including Med Students (hourly)</td>
<td>variable</td>
<td>5</td>
<td>2 to 20</td>
</tr>
<tr>
<td></td>
<td>X15</td>
<td>Nursing Staffing (hourly)</td>
<td>variable</td>
<td>4</td>
<td>3 to 25</td>
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<tr>
<td></td>
<td>X16</td>
<td>Clerical Staffing (hourly)</td>
<td>variable</td>
<td>4</td>
<td>1 to 10</td>
</tr>
<tr>
<td></td>
<td>X17</td>
<td>Orderly Staffing (hourly)</td>
<td>variable</td>
<td>3</td>
<td>1 to 6</td>
</tr>
<tr>
<td></td>
<td>X18</td>
<td>Seniority (%specialist)</td>
<td>variable</td>
<td>3</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X19</td>
<td>Medical Seniority (%specialist)</td>
<td>variable</td>
<td>3</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X20</td>
<td>Nursing Seniority (%Div)</td>
<td>variable</td>
<td>3</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X21</td>
<td>% staff on last hour of shift</td>
<td>variable</td>
<td>4</td>
<td>0-100%</td>
</tr>
<tr>
<td></td>
<td>X22</td>
<td>Doctor &quot;output&quot; per hour</td>
<td>variable</td>
<td>4</td>
<td>2 to 45</td>
</tr>
</tbody>
</table>

Table 3: ANN model parameters
REFERENCES

15. Helsinki, Swedish School of Economics and Business Administration.
Appendix C: Book Chapter published from this research (Lean Thinking for Healthcare (Springer 2013))

Chapter 3
The Suitability of Artificial Neural Networks in Service Quality Control and Forecasting
Mohammad Reza-Zadeh Niavarani and Nilmini Wickramasinghe

Abstract There has been considerable research into service quality over the last couple of decades. Services, however, as intangible, perishable, and heterogenic transactions are very difficult to quantify and measure, and little success has been reported on a systematic approach in modeling of quality of service transactions (with SERVQUAL and its derivatives as the notable exception). In this chapter, we propose artificial neural networks (ANNs) to monitor quality of service transaction as a dynamic and real-time control and forecasting system. ANNs are widely used in many engineering fields to model and simulate complex systems. The resulting near-perfect models are particularly suited for applications where real-world complexities make it difficult or even impossible to mathematically model and control the system. The proposed approach alleviates restrictions and limitations of applying questionnaire-based static methods, even in cases where there are large number of correlated attributes as well as obscure and unobservable quality characteristics. We illustrate with a case vignette in a healthcare context, thereby demonstrating the suitability of such techniques for healthcare delivery a vital, at times lifesaving service.

Keywords Service * Service systems * Service science * Service quality * Service quality forecasting * Artificial neural network (ANN) * Healthcare delivery

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N. Wickramasinghe et al. (eds.), Lean Thinking for Healthcare, Healthcare Delivery in the Information Age, DOI 10.1007/978-1-4614-8036-5_3,
3.1 Introduction

The service sector in developed countries such as the United States and Australia currently accounts for some 80% of all economic activity (DFAT 2008; Spohrer et al. 2007). The service economy encompasses not only private enterprise but also the diverse services provided by government, such as education and health care. Service systems can be described as dynamic configurations of resources (people, technologies, organizations, and shared information) that can create and deliver value to customers, providers, and other stakeholders (IFM and IBM 2008, p. 18).

Despite the sheer size of economic activities that are classified as services, service quality remains an abstract and elusive construct mainly because of its three unique features: intangibility, heterogeneity, and inseparability of production and consumption of services (Parasuraman et al. 1985). There is not even a global consensus on what constitutes quality in service transactions. One of the most comprehensive definitions of quality is the “degree to which a set of inherent characteristics fulfills requirements” (ISO 2005). In this definition, requirements are defined as the “need or expectation that is stated, generally implied or obligatory” (ISO 2005). This definition of quality is different from that usually employed in manufacturing, for example, where definition of the requirements and hence the quality are set and measured objectively by such indicators as durability and number of defects (Crosby 1979; Garvin 1983). In the absence of objective measures, subjective methods such as SERVQUAL (Parasuraman et al. 1988), SERFPERF (Cronin and Taylor 1992), and Qualitometro (Franceschini et al. 1988) have been developed and used extensively in service sector.

Computational techniques and simulation methodologies have played a significant role in modeling and optimization of production and process management over the past few decades. The lack of objective measures in services, however, has hindered adoption of simulation, control, and computational techniques in this section of the economy. There is now a clear and growing understanding amongst service scientists that there is a need for a modeling or simulation tool for services.

Artificial neural networks (ANNs) are computational networks that attempt to crudely mimic the networks of neurons of biological system such as that of humans or animals (Graupe 2007). ANNs belong to a category of meta-heuristic modeling, control, and optimization algorithms, called evolutionary algorithms (EAs). EAs are inspired by nature through exhibiting complex collective behavior from a collection of seemingly simple agents. These include ANNs, genetic algorithm, tabu search, ant colony optimization, and simulated annealing. Most of these techniques have long been used in engineering and in industry; there are reports of the application of ANNs, for example, in quality control (Abasai 2007). Their application in quality control, however, has been mostly limited to manufacturing industry. We propose there is merit in considering EAs in service quality control and service quality forecasting.
In the following section we cover service quality as it has been studied in academia, followed by an introduction to ANNs. We conclude this paper by summarizing advantage and disadvantage of using ANNs in service quality control and service quality forecasting.

3.2 Service Quality

In today’s world and in this competitive market, service enterprises attempt to achieve competitive advantage by fulfilling customers’ needs and expectations, resulting in higher customer satisfaction. Furthermore, customers’ ease of access to services and ease of supplier change have resulted in reduced customer loyalty, with the implication that service quality is more important than ever before in retaining and attracting new customers (Mahdavinia 2007).

The concept of service quality as a whole construct is large and varied. The conceptual foundation for service quality was emerged from the works of a handful of researchers who examined the meaning of service quality (Sasser et al. 1978; Gronroos 1982).

Service quality is usually expressed from a customer point of view as a function of customer’s expectations of the service compared to the perception of the actual service experience (Gronroos 1984; Parasuraman et al. 1985; Johnston and Heinke 1998). Imrie et al. (2002) showed that using service quality as a key point of market differentiation positively influenced customer retention and market growth. Interestingly, Parasuraman et al. (1988) stated that in measuring perceived service quality, the level of comparison is what a customer should expect, whereas Mahdavinia (2007) prefers that in measuring customer satisfaction, the appropriate comparison is what a customer would expect.

Some other researchers have focused on the role of employee in service quality and consequently customer satisfaction. Hartline et al. (2002) highlighted the fact that in many cases, employees are most often the first and the only representatives of a service firm to customers. Therefore, customer often base their impressions of the firm on the service received from customer-facing employees (Mahdavinia 2007).

Due to the illusive nature of service quality and its dependence on the type of services being provided, it has been suggested that managers need to understand the types of service quality factors relevant to their own services and understand various relationships between perception and performance in order to design, measure, and control the services. Service levels need to be set and strategies devised that first recognize the relative impact of individual factors on overall perceptions and secondly, link them to organization’s quality strategy (Johnston and Heinke 1998).

Overall there have been five predominant service quality measurement tools reported in literature since 1991. These tools can be summarized in chronological order as follows:
• SERVQUAL is used to measure consumer’s and service providers’ expectations and perceptions. This approach enables the exceptions and perceptions gaps to be assessed, while providing a measure of service quality gap and service delivery gap. According to Parasuraman et al. (1988) model, the gap between consumer’s expectations and perceptions is a function of several other gaps in the service delivery process (Mangold and Emin 1991). Some other models were proposed after the first introduction of SERVQUAL.

• Qualitometro (Franceschini et al. 1988) is founded on the determinants of service quality. Customer expectations and perceptions are evaluated in two distinct moments. Quality evaluation is conducted by means of a comparison between quality and expectations and perception profile. Qualitometro employs the same semantic scale and dimensions as SERVQUAL (Mahdavinia 2007).

• Two-way model used latent evaluation factors based on a survey of the theory that service quality is evaluated by answers given by customers about “objective” (quality attribute) and “subjective” (satisfaction level) (Schneeveeldt and Enkawa 1991; Mahdavinia 2007).

• Cronin and Taylor (1992) proposed SERVPERF based on their survey on theory that service quality is evaluated by perception only. The key difference with SERVQUAL is that only perceptions are evaluated (Mahdavinia 2007).

• Normed quality model (Teas 1994) uses the distinction between ideal expectation and feasible expectation to calculate service quality. It also employs the same semantic scale and dimensions as SERVQUAL. Normed is the second well-known model (after SERVPERF) that is derived from SERVQUAL (Ghoseiri and Pishdad 2006).

In addition to the well-known service quality models described above, there are other less-known models (technical and functional quality model (Gronroos 1984); GAP model (Parasuraman et al. 1985); attribute service quality model (Haywood-Farmer 1988); synthesized model of service quality (Brogowicz et al. 1990); performance-only model (Cronin and Taylor 1992); ideal value model of service quality (Mattsson 1992); evaluated performance and normed quality model (Teas 1993); IT alignment model (Berkley and Gupta 1994); attribute and overall affect model (Dabholkar 1996); model of perceived service quality and satisfaction (Spreng and Mackoy 1996); PCP attribute model (Philip and Hazlett 1997); retail service quality and perceived value model (Sweeney et al. 1997); service quality, customer value, and customer satisfaction model (Oh 1999); antecedents and mediator model (Dabholkar et al. 2000); internal service quality model (Frost and Kumar 2000); internal service quality DEA model (Soteriou and Stavrinides 2000); Internet banking model (Broderick and Vachirapornpuk 2002); IT-based model (Zhu et al. 2002); model of e-service quality (Santos 2003)).

All the above service quality models share a common feature; they evaluate quality of services through the same approach; they apply questionnaire or other data gathering tools and evaluate the quality based on their respective subjective concepts.
Many quality characteristics can be measured and stated as a numerical value. For instance, service delivery may be timed and reported in seconds or minutes or hours. These types of quality characteristics are called "variable characteristics." Advantage of questionnaire-based approaches is in their ease of collecting and the use of variable characteristics. There are, however, other types of measurements that can only assume nominal (reject, accept), ordinal (bad, good, excellent), or categorical (married, single, divorced) values. These are called "attribute characteristics." Collecting and processing of attribute characteristics are a much harder proposition as they inherit subjective principal and values. We propose the use of ANNs in order to overcome the complexity in processing these tacitly implied and subjective measurements. ANNs have been used in engineering and manufacturing, and to the best of the author’s knowledge they have not been applied in service quality control and forecasting.

3.3 Artificial Neural Network

ANNs mimic biological neural networks to model and solve a variety of problems arising in forecasting, function approximation, pattern classification, clustering, and categorization (Pao 1989).

It is estimated that there are approximately ten billion neurons in the human cortex and 60 billion synapses or connections. Synapses are elementary structural and functional units that mediate the interaction between neurons. Axons and dendrites play their role as the transmission lines and the receptive zones, respectively. Figure 3.1 illustrates the shape of a pyramidal cell, which is one of the most common types of cortical neurons. Like many other types of neurons, it receives most of its inputs through dendritic spines (Haykin 1999).

From technical point of view, the block diagram of Fig. 3.2 shows the model of neuron, which forms the basis for designing ANNs. Three basic elements of the neural model are:

1. A set of synapses or connecting links, each of which is characterized by a weight or strength of its own. Specially, a signal \( x_j \) at the input of synapse \( j \) connected to neuron \( k \) is multiplied by a synaptic weight \( w_{jk} \).
2. An adder for summing the input signals, weighted by respective of the neuron; the operation described here constitutes a linear combiner.
3. An activation function for limiting the amplitude of the output of a neuron (Haykin 1999).

The neuronal model of Fig. 3.2 also indicates an externally applied bias, denoted by \( b_i \). The bias has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively.
Fig. 3.1 The pyramidal cell

Fig. 3.2 Nonlinear model of neuron
Fig. 3.3  The structure of a multilayer feed-forward network

In mathematical terms, we may describe a neuron $k$ by writing (3.1) and (3.2):

\[ u_k = \sum_{j=1}^{m} w_{kj} x_j \]  

(3.1)

\[ y_k = \Phi(u_k + b_k) \]  

(3.2)

where $x_1, x_2, \ldots, x_m$ are the input signals; $w_{k1}, w_{k2}, \ldots, w_{km}$ are the synaptic weights of neuron $k$; $u_k$ is the linear combiner output due to the input signals; $b_k$ is the bias; $\Phi$ is the activation function; and $y_k$ is the output signal of the neuron.

The activation function defines the output of a neuron in terms of the induced load field $\Phi$. There are different activation function such as threshold function, piecewise-linear function, and sigmoid function which are applied for different types of outputs (Haykin 1999).

In terms of structuring of a network, there are different classes of network architectures including single-layer feed-forward networks, multilayer feed-forward networks, and recurrent networks (Haykin 1999). As an example, a multilayer feed-forward model is shown in Fig. 3.3.

After constructing a neural network, it needs to be trained based on some available data (different inputs and their corresponding outputs) to be able to forecast the output for future inputs with an acceptable error level through an ongoing modification process. The property that is of primary significance for a neural network is the ability of the network to learn from its environment and to improve its performance through learning. Learning is a process by which the free parameters of a neural network are adapted through a process of stimulation by the environment in which
the network is embedded. The type of learning is determined by manner in which 
the parameter changes take place. There are different types of learning including 
unsupervised learning and supervised learning. In the supervised training process, 
the user plays an important role as the network learns. However, in an unsupervised 
process the user lets the network train itself (Haykin 1999).

3.3.1 Merits and Demerits

Generally, the use of neural networks offers useful properties and capabilities 
including but not limited to (Haykin 1999):

- **Nonlinearity.** An artificial neuron can be linear or nonlinear.
- **Input-output mapping.** The network is presented with an example picked at 
  random from the set, and the synaptic weights (free parameters) of the network 
  modified to minimize the difference between the desired response and the actual 
  response of the network produced by the input signal in accordance with an 
  appropriate statistical criterion.
- **Adaptivity.** Neural networks have a built-in capability to adapt their synaptic 
  weight to changes in the surrounding environment.
- **Uniformity of analysis and design.** Basically, neural network enjoy universality 
  as information processors. We say this in the sense that the same notation is used 
  in all domains involving the application of neural network.
- **Neurobiological analogy.** The design of a neural network is motivated by analogy 
  with the brain, which is a living proof that fault-tolerant parallel processing 
  is not only physically possible but also fast and powerful.

Regardless of all aforementioned merits, neural network has the following drawbacks (Friedman et al. 2001):

- Trial and error element to building good models (in training phase).
- It is hard to interpret what is happening in the model (Black Box), and people 
  only see the inputs and outputs.
- Model performance relates to starting input values and parameters.

3.4 Application of Artificial Neural Network 
to Service Quality

In spite of considerable number of available service quality methods, there are some 
shortcomings shared between them:

1. Firstly, all proposed methods for quality control in service industry are somehow 
  subjective and they are mostly designed based on SERVQUAL. These models 
  employ static methods for data analysis. A periodical analysis can be performed
Table 3.1 A model for applying ANN in service quality

<table>
<thead>
<tr>
<th>Phase</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem definition</td>
<td>Case description, problem assumptions (service quality model, etc.)</td>
</tr>
<tr>
<td>Designing</td>
<td>Type of model, type of connections, number of layers, number of neurons,</td>
</tr>
<tr>
<td></td>
<td>activation function, cutting value</td>
</tr>
<tr>
<td></td>
<td>Estimating parameters (based on historical data)</td>
</tr>
<tr>
<td></td>
<td>Generating training data based on estimated parameters</td>
</tr>
<tr>
<td>Training</td>
<td>Training of neural network</td>
</tr>
<tr>
<td>Verification</td>
<td>Testing trained network based on random generated or historical data</td>
</tr>
<tr>
<td>Programming</td>
<td>Coding and running the network based on related assumption (cutting</td>
</tr>
<tr>
<td></td>
<td>value, etc.)</td>
</tr>
<tr>
<td>Validation</td>
<td>Validation of network in real case study</td>
</tr>
</tbody>
</table>

in a regular base (e.g., monthly, every 6 months, and yearly) if trends are to be determined. These methods are retrospective and are not able to monitor service quality in real time. Whereas, in dynamic methods, one can monitor quality of delivered service in real time (as the service is being delivered). Based on the past history (training data set), and real-time data gathering, ANNs have the ability to forecast the outcome (service quality). Exactly as humans deal with imprecise data, service quality forecasting can be performed even in the case of imprecise or imperfect real-time data.

2. Secondly, in subjective methods, the correlation between different factors is not reckoned, and each characteristic (e.g., reliability and responsiveness) is monitored through one or more questions in the questionnaire. However, in reality characteristics and attributes of service transactions do correlate and can affect service quality indirectly. Considering these characteristics in isolation ignores such indirect consequences.

3. Thirdly, in applying subjective model based on questionnaire or other means of data gathering, some variable data are missed or converted to numeric attribute. For instance, qualitative values are usually given numeric rankings. ANNs can deal with qualitative values as they are, alleviating this limitation.

Based on the above, it seems the use of ANNs for service quality control and service quality forecasting is well justified. A model for applying ANNs in service quality control is proposed in Table 3.1.

As a very general example, we assume that for controlling quality of a banking service, there are “responsiveness,” “reliability,” and “information technology” as three attribute characteristics and “time” and “cost” as two variable characteristics. Designing an ANN for such a scenario would require five input neurons and six output neurons, the first one for overall quality and the rest for showing the effect of each characteristic on the overall quality status. In this example, the output [0, 1, 1, 0, 1, and 0] means that the customer is not satisfied with the quality due to information technology and cost (“0” values).
3.5 Application to Healthcare Context

There are some different services that can be nominated in application case study, e.g., education, public transportation, banking, and healthcare. In comparison with other types of servicing, healthcare providers face many challenges, while they are concurrently under public scrutiny as consumer demands escalate. Medical care quality control and improvement as confidence in the medical community providing safe and effective patient care. Note that poor quality in patient care processes can run the spectrum from minor dietary issues to patient morbidity and fatality. It seems that applying a biological-origin concept in healthcare industry would be interesting (Frings and Laura Grant 2005). Health care is the most crucial service industry because of its nature of zero tolerance for mistakes and potential for reducing medical (Kwak and Anbari 2006). Health care is the largest service industry accounting for 17% of the US GDP ahead of education at ten percent (Larson 2009). There are about 7,500 hospitals in the United States but about 4,000 institutions of higher education (Larson 2010).

The Commonwealth Fund, in its annual survey, “Mirror, Mirror on the Wall,” compares the performance of the healthcare systems in Australia, New Zealand, the United Kingdom, Germany, Canada, and the United States. The Organization for Economic Co-operation and Development (OECD) also collects comparative statistics and has published brief country profiles as in Table 3.2 (The Commonwealth Fund 2007; Organization for Economic Co-operation and Development 2008; Wikipedia 2010).

The Institute of Medicine’s definition of quality has proved enduring usefulness: “Quality is the extent to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge” (Chassin 1998).

<table>
<thead>
<tr>
<th>Country</th>
<th>Per capita expenditure on health (USD)</th>
<th>Healthcare costs as a percent of GDP</th>
<th>% of government revenue spent on health</th>
<th>% of health costs paid by government</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>3,137</td>
<td>8.7</td>
<td>17.7</td>
<td>67.7</td>
</tr>
<tr>
<td>Canada</td>
<td>3,895</td>
<td>10.1</td>
<td>16.7</td>
<td>69.8</td>
</tr>
<tr>
<td>France</td>
<td>3,601</td>
<td>11.0</td>
<td>14.2</td>
<td>79.0</td>
</tr>
<tr>
<td>Germany</td>
<td>3,588</td>
<td>10.4</td>
<td>17.6</td>
<td>76.9</td>
</tr>
<tr>
<td>Japan</td>
<td>2,581</td>
<td>8.1</td>
<td>16.8</td>
<td>81.3</td>
</tr>
<tr>
<td>Norway</td>
<td>5,910</td>
<td>9.0</td>
<td>17.9</td>
<td>83.6</td>
</tr>
<tr>
<td>Sweden</td>
<td>3,323</td>
<td>9.2</td>
<td>13.6</td>
<td>81.7</td>
</tr>
<tr>
<td>United</td>
<td>2,992</td>
<td>8.4</td>
<td>15.8</td>
<td>81.7</td>
</tr>
<tr>
<td>Kingdom</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>United States</td>
<td>7,290</td>
<td>16.0</td>
<td>18.5</td>
<td>45.4</td>
</tr>
</tbody>
</table>
Some operational inefficiencies are associated with the direct medical service delivery process. Others are associated with the administrative, logistical, and operational side of the healthcare delivery system. Both areas can benefit from systematic process innovation activities (Henk de Koning et al. 2006).

A lot of different attributes and variable quality characteristics can be considered in healthcare to monitor, predict, and improve (Loey Schwall and Camille De Yong 2003; Richard Stahl et al. 2003) the notion that the quality characteristics in healthcare can be classified into four categories:

- Service level (e.g., access to care, wait time, service time)
- Service cost (e.g., cost per unit of service, labor productivity)
- Customer satisfaction (e.g., patient or family, referring physician, employee)
- Clinical excellence (e.g., guidelines for medication or treatment, standard procedures for patient monitoring)

From a different angle, McGlynn et al. (2003) proposed different quality indicators in three types of care including preventive, acute, and chronic and in four different functions including screening, diagnosis, treatment, and follow-up. In an analytical paper published by the Quality in Australian Health Care Study (QAHC), Ross McL Wilson et al. analyzed the cause of adverse events resulting from healthcare in Australia from different categories like human error categories, delay categories, treatment categories, and investigation categories (Ross McL Wilson, Harrison et al. 1999).

### 3.6 Concluding Remarks

Service quality and methodologies of measuring it were discussed and then from the case vignette contextualized for a healthcare context. In this way, we demonstrated the potential benefits of applying ANN into healthcare to facilitate the achievement of superior healthcare delivery. The gaps in the currently available methodologies were highlighted. Based on the lessons learnt in manufacturing dealing with analogous problems, the use of evolutionary algorithms (EAs) in service quality control and forecasting is proposed, and a simple model for applying ANNs (a subclass of EA) is presented.

For completeness, it is noted that the application of ANNs in service quality control and forecasting has the following characteristics:

1. No restriction on the type of inputs and outputs (qualitative values, quantitative attributes, or any combination thereof).
2. No assumption is made on the statistical distribution of variables and their interdependence.
3. No limitation on the number of inputs and outputs (although it is noted that as the number of inputs and outputs increase, the network might become prohibitively complex).
4. No requirements on access to large data sets. EV can be trained and used with much smaller data sets than statistical methods afford.

5. Computationally very efficient, which can translate into much faster data analysis; affording near real-time data analysis in the case of ANNs.

We believe ANNs are a prime candidate in service quality control and service quality forecasting. Research is already underway in designing and applying an ANN as a dynamic model for monitoring and forecasting of service quality in a nominal service industry. Further, ANNs have the potential to bring numerous benefits to healthcare contexts and we close by recommending their incorporation into healthcare contexts.

References


Appendix D: Student’s another PhD Thesis – The university of Melbourne (2014)

Multi-variate-attribute quality control (MVAQC)

Download
- Multi-variate-attribute quality control (MVAQC) (3.323Mb)

Document Type
PhD thesis

Access Status
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Description
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Multi-Variate-Attribute Quality Control (MVAQC)

by

Mohammad Rezazadeh Niavarani

Submitted in total fulfillment of the requirements of the degree of Doctor of Philosophy

July 2014

Department of Mechanical Engineering

The University of Melbourne