Considerations on modeling for early detection of abnormalities in locally autonomous distributed systems
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Chapter 1

Introduction

The automation and evolution of networked applications brought locally autonomous distributed systems with global quality attributes. These systems have moved beyond acceptable manageability. Both design and application are unavoidably imperfect due to the complexity of modeling and consequently systematic errors appear. The classical detection approaches are limited in their coverage. Hence, to advance the state of the art, a better understanding is needed of the requirements for early abnormality detection in locally autonomous distributed systems with global functions.

In this chapter we introduce the motivation and background concepts required for the discussion of early detection of abnormalities in locally autonomous distributed systems. The need for detection occurs when a system does not fit well in its embedding environment. This may be because the environment was not fully understood when the system was designed or because it has simply changed since then. Things can get out of hand when the system reacts according to a wrong perception of the world around it. Detection is then brought into play to avoid such misbehavior. In section 1.1 we discuss the application domain of Locally Autonomous Distributed Systems (LADS) with global quality attributes, which raises the issue of modeling and detection. The classical detection framework, classical methods and techniques, are introduced in section 1.2. Finally, in section 1.3 the objective, the problem and the related research questions addressed in this thesis are explicitly stated.

1.1 Automating beyond control

1.1.1 The challenge

We have become highly dependent on very complex man-made distributed systems for energy production and transport, communication, environmental monitoring and industrial production. These increasingly automated systems are growing beyond manageability. Many strategies and techniques, though well-founded on physics and mathematics, do not provide a system design that is correct-by-construction. To make imperfection acceptable, the involved risks in terms of cost and potential harm to others demand at least an adequate approach to prevent the worst to the largest affordable extent. Methods well-founded on physics and mathematics often fail to provide an adequate approach to accommodate a priori unknown but actual imperfections, which is why computational intelligence is called upon. The alarming observation is made that the well-founded arsenal, including rigorous exact modeling, fails to bring sufficient manageability and sufficiently predictable behavior of the increasing complex man-made systems that have become the fabric of our society. This poses the challenge that we take up in the coming discourse.
1.1.2 The complexity of distributed systems

Welfare has increased in the previous century through the expansion of Signal, Electricity, Water and Natural Gas Grids. A recent addition is the Information Grid (or Internet). This does not only enrich the classical networks, but also stimulates new sensory ones in Home and Industry [Amin, 2002]. The default distribution of a programming error as part of the maintenance procedure, that in 1992 causes the New-Jersey blackout, may have seemed just an exception at that time. But the problems keep coming back. Foremost the Allston-Keeler (July 1996) and the Galaxy-IV (May 1998) disasters gave rise to a concerted research activity on Self-Healing Networks [Amin, 2000]. In general the probable cause is a lack of investment to ensure proper operational conditions as a result of commercializing national and global responsibilities. The series of three disasters on the Electricity Grid in Autumn 2003 (in respectively America, Sweden and Italy) suggests that little progress has been made. And this is only the tip of an iceberg [Amin, 2003; Barabasi 2003].

Predictable behavior is key to prevent malfunction. In energy Grids, the EC recently called for EU wide governance. It is already a national concern, and for good reasons. These networks grow without an overall architectural vision but rather by means of a local preferential attachment. Despite the lack of predetermined structure a seemingly chaotic self-organization leads to a structure, though often surprisingly different from the topology of designed networks [Barabasi, 2003]. Automation brought LADS, which displays seemingly unpredictable behavior. What led to this situation?

Figure 1.1 : Jacquard pattern looms in the factory Gevers & Schmidt in Schmiedeberg (Silesia). The pattern is entered via punched cards. (Wood engraving from 1858, · Deutsches Museum, München)

Expansion of man-made systems and industrial automation is an interaction of market-pull and technology-push. Industrial automation has a long history starting with the advent of machines driven by windmills in the Dutch Zaanstreek in the 17th century, over automation in the spinning and pattern weaving industry (figure 1.1) via the production streets popularized by Ford in the early 20th century to semi-automatically managed energy production and distribution systems. In automated processing the pursued short time-to-market and technology adaptive-
ness induces rapid replication of errors: "in ultra-dependable systems even a small correlation in failures of the replicated units can have a significant impact on the overall dependability" [Bouysoussoune & Sifakis, 2005]. The accumulation of such deviations into an harmful failure must be prevented by a pro-active rather than a reactive attitude.

The network concept has moved in various directions. Sensory networks have become prevalent in Home and Industrial Automation. They display a high degree of heterogeneity, which adds to the system complexity and therefore implies reliability problems [Bullinger, 2004]. In the evolution of ever more complex and more automated systems, the risks in terms of damage and cost increase. These risks are unacceptable when a potential disaster is at hand, no matter what the probability is. Risks are highly inconvenient when they touch upon our well-being, such as by a loss of electric power, communication or public transport. They are merely undesirable and costly when the performance and availability of a system or instrument do not meet targets. In the economy of industry and governmental responsibility, investments follow risk-management strategies. The quality of a product or service is expressed in probabilities; imperfection is a design criterion, dictated by return-on-investment. The prevailing risk-management strategies optimize but not minimize the failure probability.

We have a responsibility for the man-made technological systems exploiting natural principles and resources. Such is in the hands of those who can perceive the patterns, rather than the unaware actors within the system. Responsibilities, besides those economically motivated, concern prevention, precaution and at least minimization of potential harm by guarding and guiding the environment. "A grand challenge for science is to understand the human implications of global environment change and to help society cope with those changes. Virtually all the scientific questions depend on geospatial information. Another challenge is to respond to calamities, terrorist activities, other human-induced crises, and natural disasters. Much of the work addressing environmental- and emergency-related concerns will depend on how productively humans are to integrate, distill, and correlate a wide range of seemingly unrelated information" [National Research Council, 2003]. Next to the responsibility for man-made systems there is an increasing demand to monitor ecosystems both for economic and safety purposes. Geospatial sensory networks can offer early warning for earthquakes on land or in the ocean that may cause tsunamis. However early detection depends on detecting and localizing patterns without exact, physically plausible models. The resolution and coverage of sensor networks are rapidly increasing, causing an overwhelming stream of data. The intelligence of human interpreters needs to migrate into automated systems.

Complex distributed systems become monoliths through attachment. Systems that are initially isolated become super-systems when distinct inseparable global functions and qualities are pursued. Other systems are intentionally designed for global functions and qualities, e.g. the new generation of radio-telescopes LOFAR and SKA. Global functions are eminent, while distinct sub-functions are no longer isolated in sub-systems; these types of systems are really different from classical FDI (Fault Detection and Isolation) applications like airplanes, and isolated chemical systems and power plants. Distributed systems with global functions differ

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1. The word sensor network refers to the system or platform, it is a network with sensors. The word sensory or sensing network is used for applications which pursue to benefit from the combination of sensor signal. In the sensory network concept a central model of an observed entity is calibrated using the sensor data. Sensory networks are sensor networks, but a sensor network is not necessarily a sensory network. We have used the concepts indiscriminately, their meaning will be clear from the context.
from robots, where the vision and the arm-movement are different sub-systems with a distinct function. This has major implications for the quality management, since it is no longer clear how the quality of sub-processes contributes to the quality of the end-product; it is hard to analyze global quality aspects as the disturbance propagation is very complicated.

Distributed systems with global functions demand a coherent co-operation. Control mechanisms are an integral part in most dynamic systems, guiding them towards desired behavior. Control is designed purposefully into systems. In ecosystems the dynamics result from facilitation and competition over resources. Where craftsmanship turns into automation using machinery, human-guided processes and machines further evolve to connected distributed systems. In the expansion appears an increasing effort to steer the interaction of components, as human-operations are replaced by hierarchical PID-control. Increased organizational complexity and accurately timed closed-loop control appear in local processes. Consequently global direct control over all components is in many instances no longer possible, resulting in autonomous subsystems. Local autonomous processing and the hierarchical distribution of set-points allow for this. In a new generation of distributed systems, self-organization appears. Who manages the consequences of these developments on the requirements for health monitoring?

1.1.3 The complexity of modeling

There is mathematics (a truth but only within itself), there is statistics, and there is artificial intelligence. These three areas have struggled and competed in an ongoing effort to describe the world as we see it with the ultimate goal of control through technological advances. Ever since the industrial revolution we have become increasingly dependent on technology. It is inevitable that we slowly have recognized the limitations of our understanding of the processes in an effort to describe and control. Many processes are not well understood and confront us with unforeseen events and unexplained behavior, often to our detriment. We observe, sample and store huge amounts of measurements, but conventional models and modeling techniques fail to increase our understanding in the complex behavior of the underlying processes.

A system design starts from a conceptual, desired function. The expertise to construct a model may have been assembled over a long time and formulated into generally valid natural laws, such as Ohm's Law or Maxwell's equations. Engineering always puts a strong emphasis on the ability to formulate the exact model for design purposes. Such a model can be used as a frame of reference. Future developments will have the model as common starting point, describing a common understanding for all concerned. The model derived from first principles is often assumed to suffice for design and control purposes.

A case of modeling complexity: designing the new generation of radio-telescopes

The Dutch low-frequency array (LOFAR) is a new type of telescope for conducting radioastronomy at low frequencies, with large instantaneous bandwidth (32MHz) and unprecedented sensitivity and resolution and multi-beaming capability. The LOFARs infrastructure is also utilized for several sensor network applications. The essence of LOFAR is a coherent acquisition and processing of data to fit accurate dynamic models of natural phenomena approximately in real-time. We have conducted the feasibility and preliminary design studies for the LOFAR stations, and as such participated in the system group. The LOFAR design objectives are a typical challenge to squeeze the most out of emerging technology capabilities to provide, within a limited budget, a highly competitive and unique multi-purpose facility to a demanding and critical
customer. All the digital subsystem design issues are highly intertwined with the design and issues of analog/RF front-end and the backend signal transport and central processing. The use of a global system model that leaves the necessary room for options to be offered by emerging technologies is used in the subsystem design. The lack of a very detailed system design is a threat to the convergence of (a) the system design studies and requirements, and (b) the system specification discussions. We have a collective learning process where unknown subsystem properties need to be integrated successfully into a large system. A detailed end-to-end simulation, to that purpose, has been advocated but was never achieved. These experiences show that an adequate system model is already beyond reach in design, despite a competent and focused team effort.

The difficulties in modeling locally autonomous distributed systems

The difficulties in modeling arise from the complexity of system behavior: dependencies appear where they are not expected and variability occurs instead of consistent and predictable behavior. Either way time-variant behavior is a rule rather than exception, and abnormalities have to be identified from volatile measurements. The essential difficulties that are generally agreed upon, are: hidden dependencies [EEUMA, 1999]; variability [Venkatasubramanian, 2003]; and, interaction of a system with an unknown environment [Lisboa, 2001].

A common remedy: divide and conquer

A fine-grain exact model for design and control implementation is too complex for large systems; therefore feasibility (both of the design as well as in the control) depends on a divide-and-conquer approach. A system is composed hierarchically out of subsystems, subsystems out of sub subsystems, etc. down to a level of detail where desired function, form and resulting behavior coincide. This is the level of logical or physical components. On this level of abstraction, where desired function, form and behavior coincide, a model is derived straightforwardly from logical or physical principles.

1.1.4 Deviations and disturbances

Deviations are differences between the behavior that can be explained from the model and the actual system. A model is as good as the supporting measurements. Consequently reality may be different from the design concept and disturbances may occur, as: 1) measurements are influenced by other than the intended subset of measurements; 2) models are incomplete, i.e. they do not describe the process or entity as it is, and 3) measured processes and entities are subject to change. Usually these effects are present simultaneously and cannot be easily isolated in their net effect. Though the different ingredients of disturbances are modeled with varying levels of detail, it is generally agreed upon that two types of disturbances can be distinguished: unstructured and structural errors. Random errors cannot be prevented, as they are unstructured by definition. There is no meaningful extension or alteration to the existing model to reduce such problems. Unstructuredness can result from numerical imprecision, chaos and inseparability of a single data source out of the many influencing the measurements.

The model should remain a good representation of the data source, hence it must accommodate systematic errors. Therefore we need to recognize the conditions, under which the model can be improved. If there is a source of disturbances in profound interaction with the data source, it will cause structural dynamic disturbances that evolve towards unacceptable performance degradation. Revealing the presence of such sources is the goal of this research.
1.1.5 The function of detection

The purpose of fault detection, diagnosis and accommodation in real-world applications are: 1) to increase availability of the production process; 2) to enhance efficiency of the production process; 3) to improve safety of the process; 4) to increment quality of the end-product or provided service. Detection is a function complementary to the systems nominal operation, aiming at accommodation of deviations which are not treated by the systems control. Detection of disturbances facilitates the identification of wear, damage and other changes in the process.

1.2 Detection approaches

1.2.1 The classical framework

Detection is decision making or rather hypothesis testing based on a residual error signal. The following steps are generally agreed upon to make a decision:

1. model: to represent the known and expected behavior;
2. sign: to compute an efficient representation of the residual;
3. compare: to compare signatures of different measurements of presumed behavior;
4. decide: to use information from the comparison(s) establishing the factual discrepancy.

![Figure 1.2: Isermann’s framework for detection and diagnosis [Isermann, 1984]](image)

The, by now paradigmatic, framework for detection is shown in figure 1.2. At it’s heart is the physical-principle model, which through state and parameter estimation allows for a transfor-
mation of measurements to physical properties or so-called non-directly measurable quantities (NMQ). These physical properties are interpreted and classified and yield a diagnosis including the location and cause of fault in case it is present.

1.2.2 Strategies and techniques

Two partitions divide diagnostic methods into four categories. The first partition separates process-oriented (white-box) approaches from process history based (data-driven) approaches. The second partition separates qualitative methods from quantitative models. Detection and diagnosis techniques are classified [Venkatsubramanian, 2003] into these categories. The qualitative techniques are: 1) causal models and abstraction hierarchy; and 2) expert systems and quantitative trend analysis. These approaches are not considered in this research. We consider approaches that rely on both a model as well as measurements. These approaches are divided three ways: 1) residual vs. parameter-based (figure 4.4); 2) data-driven vs. process-oriented; 3) self-organized vs. supervised estimation; (figure 4.3 illustrates the latter two classifications).

Residual-based vs. parameter-based

In a residual-based approach, the error of the model is directly used to compute signatures. In parameter-based methods the parameters of a model serve to compute the signatures. Estimation is essential in parameter-based signature computation. In case the model is a priori incomplete, on-line observations are required to calibrate the model to keep it up-to-date.

Process-oriented or white-box modeling.

A key assumption that underlies the classical detection approach is: Given an optimally controlled system the residual can be assumed to be stationary. If not, there is an abnormality. Given the state-space equations, derived from quantitative physics, the system designer can reach optimal control by forcing equilibrium in state space. Quantitative techniques that will be considered in chapter 4 are: dedicated observers, parity spaces and Kalman filters.

Data-driven and black-box modeling

A contemporary problem in both process control and identification as well as in data-mining is that in many situations there is no clear notion of an underlying process which can be modeled by a physically plausible process model while there is a huge amount of data. In contrast to a model-based approach, computational intelligence is founded on data-driven approaches. They allow for descriptive model construction in the absence of physically plausible process models.

Self-organizing vs. supervised fitting

Parameter-based methods fit measurements pursuing a specific functional relationship. This is reflected in the coding problem (input-target) and the model architecture. This form of estimation is called supervised. The process-oriented parameter-based approach is supervised. Black-box models can be supervised as well as self-organized. Unsupervised estimation is an unrestricted adaptive projection of data. They are founded on PCA (principal component analysis) pursuing a best linear separation between signal and noise space. It allows for a blind analysis of any dynamic and static dependencies between possibly hidden features. Kohonen maps and ART (adaptive resonance theory) are examples of self-organizing neural models.
1.2.3 Principal challenges

Key detection and diagnosis performance criteria are [Venkatasubramanian, 2003]: sensitivity; promptness; isolatability; robustness; novelty identifiability; a quantified figure of merit; adaptability, explanation facility; modeling requirements; storage and computational requirements and multiple fault identifiability.

Fundamental trade-offs in the criteria are [Isermann, 1984]: the size-of-fault vs. the required detection-time, the speed of fault vs. process response time, the speed of fault vs. detection time, the size and speed of faults vs. maximal speed of process parameter changes and the detection time vs. false alarm rate. The crucial trade-off is promptness vs. robustness: the stationary window vs. analysis or detection window. Or, to put it differently, the number of measurements for establishing the abnormality needs to be sufficient to fit a model confirming it’s presence with sufficient confidence.

There is a key trade-off between robustness to various noise contributions & uncertainties, and isolatability. Under ideal conditions, having freedom from noise and modeling uncertainties, the detector should project measurements onto a space where output response is orthogonal to faults that have not occurred. To obtain a signal trend that is not too susceptible to momentary variations due to noise, some kind of filtering needs to be employed. Filters suffer from the fact that they cannot distinguish well between a transient and a true instability [Venkatasubramanian, 2003]. Systems designed to respond quickly to certain abrupt changes must be sensitive to high-frequency effects, hence they are more sensitivity to noise. [Wilsky, 1976].

There is a trade-off between sensitivity and promptness vs. novelty identifiability. One has access to a good dynamic model but it is possible that much of the abnormal operations region may not have been modeled adequately. The timely reaction of a detection algorithm may be impaired by the desire to handle various kinds of a priori unknown abnormalities (Universality). Conventional process-oriented FDI relies on a comparison of reality with a pre-developed model of the ideal process to facilitate a swift decision-making. Supervised learning raises the sensitivity by modeling a range of faults on the basis of "golden" (desired and ideal) behavior, while a level of self-organization suffices for monitoring. A trade-off to optimize for an appropriate choice of design parameters determines the success of any detection approach.

1.3 This research

This research focuses on an intersection of the detection challenges in relation to properties of LADS (locally autonomous distributed systems) with global functions. We offer a new perspective, in the scope set by this intersection, positioning several new ideas in a coherent analysis. This dissertation provides new understanding that is supported by a synthesis of requirements from an analysis of the limitations of the existing "classical" arsenal.

1.3.1 Research problem

Our problem is to detect early, to identify a change before it becomes a fault or a failure. This problem is the detection of systematic deviations before they result in undesirable states in LADS within the global function and quality objectives.
1.3.2 Research objective

Our objective is improved understanding of design aspects of a detection procedure: identification of the properties of the detection problem (properties of system and abnormalities), leading to selection of a detection strategy and techniques, and an evaluation of potential (dis)advantages for required innovation.

1.3.3 Research questions

The key question of this research is: “Is a disturbance the result of a system that changes toward an undesirable state or of an incomplete model?”. We seek an answer by investigating:

1. If it is possibility to identify the presence of a priori unknown potentially harmful structure from time-variant behavior?
2. What are the limitations of the existing arsenal of strategies and techniques?
3. What causes the limitations of the existing strategies and techniques? How do they relate to properties of the detection problem (features of system and abnormalities)?
4. Can neural networks offer a solution by modeling the dynamics in the data utilizing their on-line learning capabilities.

1.3.4 Thesis

Despite the physical and mathematical foundation of the disciplines involved in system design and operation, the pragmatic industrial R&D sections have opened up to less conventional techniques, i.e. computational intelligence, to complement the existing arsenal. Computational intelligence includes quantitative methods such as neural networks, fuzzy logic and evolutionary algorithms. Our research originates from this setting, i.e. to investigate the potential merits of neural networks to detect and reduce time-related disturbances in batch-oriented processes.

Modeling real-world systems while pursuing physical plausibility has scarcely increased the understanding for coping with the unexpected. Our quest is to identify unexpected patterns directly from behavior, instead of through after-the-fact analysis of a physically plausible model. We consider whether neural networks are usable for this purpose.

1.3.5 The role of neural networks

Detection based on physical principle models pursues accurate diagnosis by exploiting a strong relation between the topology of the source and the architecture of a detection model. As fine-grain modeling from the physical principle models is neither effective nor strictly necessary for design purposes the accurate model is often not available for operational system monitoring. Nonetheless huge amounts of monitoring data needs to be inspected for early detection and failure prevention. Computational intelligence provides models to identify patterns in data. We have chosen multi-layer Perceptrons since these neural networks can serve as process models of dynamical systems which is not obvious for other models. Moreover their supervised gradient-based adaptation allows for a preferred parameter based detection.

This thesis considers the features of neural network black-box modeling for detecting abnormalities in complex and large data sets, seeking an effective comparison of data in the absence of a physically plausible model. We focus on neural networks because of three particular features: self-organizing internal behavior; associated continuously and iterative adaption procedures; and the ability to the approximate continuous functions. They offer a middle way
between gross simplifications and complexity explosion by providing a model to inspect dependencies at an effective and efficient level of detail. Redundancy is often used for recognition purposes. Recognition is improved by comparing multiple independent representations of the same entity. Nature provides inspiring examples of this mechanism. We will exploit the benefits of redundancy inside the neural model.

1.4 Thesis layout

1.4.1 Outline

This thesis contains two parts. Part I is primarily a classification of the prior art covering dynamical modeling of systems and disturbances, and detection theory. It includes a basic understanding of modeling and estimation of systems and signals (chapter 2); dynamical neural networks (chapter 3); understanding neural design and neural learning (chapter 3), and understanding the arsenal of detection strategies and techniques (chapter 4). Part I equips us with a solid background on modeling for detection, both physical principle and statistical approaches as well as at least one example of an alternative to mathematically founded approaches: neural networks that detach the modeling from any assumed physical or logical laws. Part II covers a new perspective on the required modeling for early detection and an analysis of the problems and synthesis of requirements. Part II consists of an problem analysis inspired from real-world phenomena (chapter 5); a synthesis of the essential requirements and key design trade-offs (chapter 6); and an exploration of a neural solution (chapter 7 and 8).

Chapter 2 introduces the basics of modeling and estimation of signals and systems. We assume familiarity with such basic techniques and issues in part II of the thesis. It discusses the techniques for data analysis and problem coding, the basic issues concerning model complexity, and fundamental limitations such as solvability and observability.

Firstly, chapter 3 introduces neural modeling to capture dynamics in data and new patterns in systems and data. The principle mechanisms are time-series modeling and accommodation. We provide a classification of dynamic neural networks [vanVeelen, 2000a] and an evaluation of neural temporal PCA [vanVeelen, 1999]. Secondly, chapter 3 introduces neural network features that clearly distinguish them from classical modeling approaches, i.e. physical principle and statistical modeling. Chapter 3 also addresses neural design issues, relating symptoms to neural features, linking it to remedies and applied neural metrics. These neural metrics reappear in chapter 8 when we consider neural modeling and signature computation from neural learning behavior for early detection.

Chapter 4 provides a survey of methods and techniques found in signal detection and FDI, resulting in a classification of methods that relate the properties of abnormalities and systems. We discuss reasons to apply computational intelligence in detection including possible scenarios to apply learning for detection [van Veelen 2000b].

Chapter 5 is an analysis inspired from an exploration of the phenomena in the design and use of LADS. We discuss the causes of limitations of the classical detection arsenal [van Veelen, 2004, 2005]. A key contribution is the increased understanding of the gap between the nature of abnormalities occurring in practice and the capabilities of classical detection approaches.

Chapter 6 provides the motivation for the set of essential modeling requirements to address the early detection problem, synthesized from the identified limitations and their causes.
The procedures discussed in the intermezzo (chapter 7) are not a part of the thesis theory (which is on the modeling requirements rather than on a specific detection procedure). The techniques and procedures in chapter 7 are given without further proof. In chapter 8 we argue the potential of neural modeling and estimation to meet the modeling requirements. It discusses neural features in relation to the derived requirements, we illustrate the required neural capability [van Veelen, 2000c, vanderSteen 2001] in addition to some recent publications in our problem domain.

1.4.2 Pointers to related work discussed in this thesis

We have not discussed the related work for the topics of this thesis in isolation since the related work is quite extensive and diverse. Instead we provide a few pointers here to the related work discussions found in various contexts throughout the thesis. A discussion of work by others on the investigated techniques and methods is found in:

- Section 2.2.2 discusses methods for time series analysis.
- Section 2.3 provides a short overview of various methods to model systems and data.
- Section 3.4.4 provides a survey of metrics for the analysis of learning in neural networks.
- Chapter 4 is a literature survey of conventional methods for detection.

The discussion on work by others comparable or directly related to this research is found in:

- Section 4.4.3 provides an overview on the use of neural networks in a conventional detection approach, i.e. the neural network does not replace the conventional system models.
- Section 5.2 includes references to published application specific research for the cases.
- In section 7.4 we discuss those methods that also seek alternatives to overcome limitations of the conventional approaches, either using a similar model or using a similar approach for detection or diagnosis.

Furthermore comprehensive discussions on work of others related to the various topics in this thesis can be found in the published papers, listed in appendix G.2.1, related to this research.