End of Module Assignment

Prospects for AI Fault Diagnostics and

Remediation in Eskom Telecommunications' Networks

Introduction and Background

Modern Computer systems are creating and using more and more data in an accelerating trend through special-purpose and general-purpose computers (Cisco, 2020). The source of this enormous data production can be attributed to a multitude of software systems, running on computing machines in various sectors of a society that is computer-dependant and highly connected the world over (Maniewicz, 2020). In the business sector information and data are increasingly relied upon to function efficiently and ensure business needs are met (United Nations, 2019). Due to the huge growth in data production a commensurate need for communication networks to move data between processes running on distributed and standalone systems has arisen (IEEE Communications Society, 2021). Accommodation of the necessary traffic throughputs and associated services has led to Communication service providers now needing to deal with vast expansion requirements, in addition to various network fault and monitoring challenges (Abbasi et al., 2021).

Eskom is a major energy supplier for South Africa, generating approximately 90 percent of the total electricity for the country (Department of Energy: Republic of South Africa, 2019). The author works as a technician for Eskom Telecommunications (ET) which is the communications division of Eskom (Eskom, 2021a).

ET has a geographically expansive backbone network consisting of fibre optic and microwave radio technologies which cover the majority of South Africa (Eskom, 2021b). Furthermore, they are an enabler of mission critical and support services for various business entities within the organisation, through a variety of platforms (Eskom, 2021a). Some of their major service offerings include: Point-to-point Time Division Multiplexed (TDM) or packet switched connections, for the Information Technology (IT) division's Wide Area Network (WAN) and Local Area Network (LAN) infrastructure; Voice over Internet Protocol (VoIP) telephony; two-way radio voice communications; and multiple Supervisory Control And Data Acquisition (SCADA) connections (Eskom, 2021b). Their services are largely focused within layer 1 to 3 of the Open Systems Interconnection (OSI) Reference Model, with a comparatively small end-to-end service provisioning (Cisco, 2005).

Problem Statement

ET currently relies on traditional methods for network monitoring in terms of system health and fault reporting (Krinkin et al., 2020). Additionally, historically applied methodologies are also used for network fault diagnostics and repair, to meet Service Level Agreements (SLAs), and maintain overall performance levels of the vast interconnectivity provided (Krinkin et al., 2020). This approach leans heavily on proprietary Network Management Systems (NMSs) developed by Original Equipment Manufacturers (OEMs) which are superficially and operationally disparate as well as disconnected from one another, therefore not operating in unison (de Greve & Piplani, 2017).

The NMSs generally in the form of server software, run on Virtual Machines (VMs) which reside on computers at centralised Network Management Centres (NMCs), where they are used to aggregate received information generated by equipment dispersed throughout various physical locations (International Telecommunication Union, 2000). Please see Figure 1. Information received is presented to personnel through a front-end system, in a holistic network representation (Cisco, N.D.a). Signals are also generated via the system supporting the server software, upon the server’s request (Cisco, N.D.a). These signals remotely instruct special-purpose machines in the form of telecommunications equipment in the field, via the associated networking technologies. Many signals sent from the server software are due to front-end application triggers, made through a Graphical User Interface (GUI) by technicians remotely managing equipment (Cisco, N.D.a).

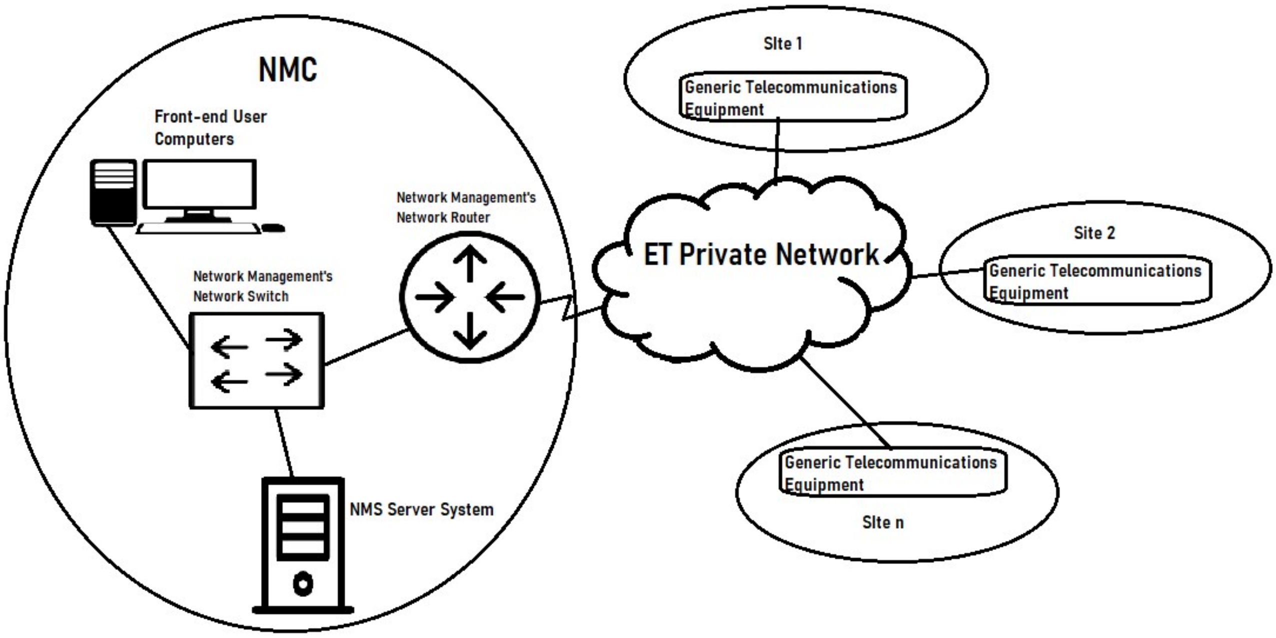

Figure 1 - Network Monitoring Setup

Figure 2 below represents a simplified yet holistic depiction of the current fault management process. One will conclude the following points from observing the figure:

- No fault predetermination is available where equipment metrics are analysed and deterioration trends pointing to a high probability of fault occurrence flagged. Faults are only raised as a reactive measure (Gurer et al., 1996).
- There are little self-healing capabilities where different network elements can be instructed to perform activities to enable continued system functionality whilst a fault is being repaired. Only layer 3 equipment like routers running distributed applications such as the Open Shortest Path First (OSPF) routing protocol have sufficient intelligence to perform rerouting operations (Moy, 1998).
- The fault management process can be labour intensive, as there are many steps to be performed by various parties (Rao, 2011).

- Scaling is a problem, as multiple faults require multiple personnel to separately complete their own fault management flow.
- Intelligence in terms of root cause analysis is applied purely by humans, without any computer aid (Rao, 2011).

Due to the aforementioned observations, the following are points of concern:

- The current model is very reactive (Rao, 2011).
- If no rerouting is possible service failure is highly probable.
- Resource use can be unnecessarily high if a fault is incorrectly diagnosed, and a local technician is deployed to site when not required.
- NMC personnel will have to queue additional faults when all staff have already been allocated a fault to deal with.
- Interrelated faults but on separate systems are not flagged as such.
- There is little intelligent computer aid in terms of root cause analysis and for the process as a whole (Gurer et al., 1996).

In summary, although there is support during faults by some technologies like OSPF at layer 3, there is not much intelligence for equipment providing services at layer 1 and 2 (Cisco, 2005). Furthermore, the telecommunications network topology may need the implementation of a more meshed design philosophy, but even if that were the situation the decision-making processes for service reprovisioning in a fault situation is still required (University of Essex Online, 2021a). Additionally, NMSs do not interconnect to provide a holistic view of network layers and possible interrelations. Lastly, there is little to no fault predetermination, and hardly any computer-aided fault diagnostic support mechanisms (Gurer et al., 1996).

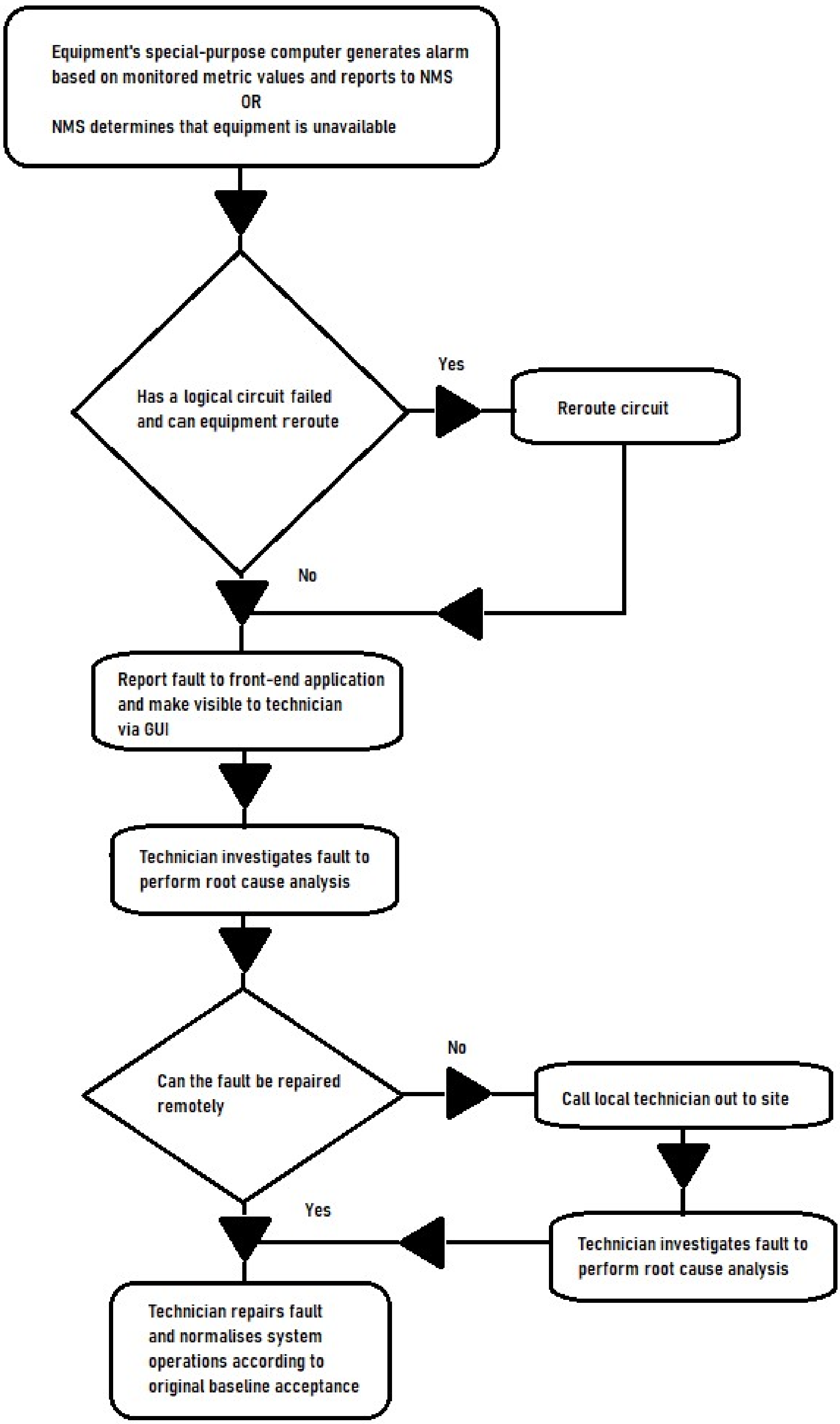

Figure 2 - Fault Management Process

Literature Review and Solution Proposal

Sophisticated manifestations of narrow Artificial Intelligence (AI) in computer systems provide a powerful tool (Brookshear & Brylow, 2018; Allen & Darrel, 2018). Encoding superficial reasoning capabilities allows complicated decision-making processes, like in the case of that required in the fault management process described in the problem statement, to be performed by computers (IBM, 2020a). For instance, fault predetermination could be done by an Agent program periodically analysing ET network's equipment sensors' related metrics, to create a trend analysis, and then calculating the probability of an issue arising (Brookshear & Brylow, 2018; Allen & Darrel, 2018). Furthermore, AI has seen a resurgence over the last decade, largely due to advancements in compute power, dataset availability, and algorithm development (Kepner & Gadepally, 2020). Therefore, many companies worldwide are seeking to leverage the associated technologies to increase business productivity and minimise costs, consequently further driving advancement and solution availability (United Nations, 2019).

In telecommunications and the more general field of Information and Communications Technology (ICT), various vendors are using or aiming to use AI and its more specialised techniques and algorithms associated with Machine Learning (ML), Artificial Neural Networks (ANNs), and Deep Learning (DL), for a multitude of tasks including network monitoring, and traffic analysis (Cisco, N.D.b; Ericsson, N.D.a). ML is the principle of creating algorithms which enable computer systems to learn from data, and thereby become more accurate without explicit human intervention in the form of additional programming (IBM, 2020b). ANNs represent a model for an algorithmic technique used to perform ML, in which computer systems are able to be more efficient when processing large amounts of data (Alaloul & Qureshi, 2020). DL refers to an ANN which is constructed of more than three node layers, but more importantly enables the associated algorithm to be less dependent on human intervention for learning (IBM, 2020c). Figure 3 below is a Russian Doll depiction of the relationship between AI, ML, ANNs, and DL.

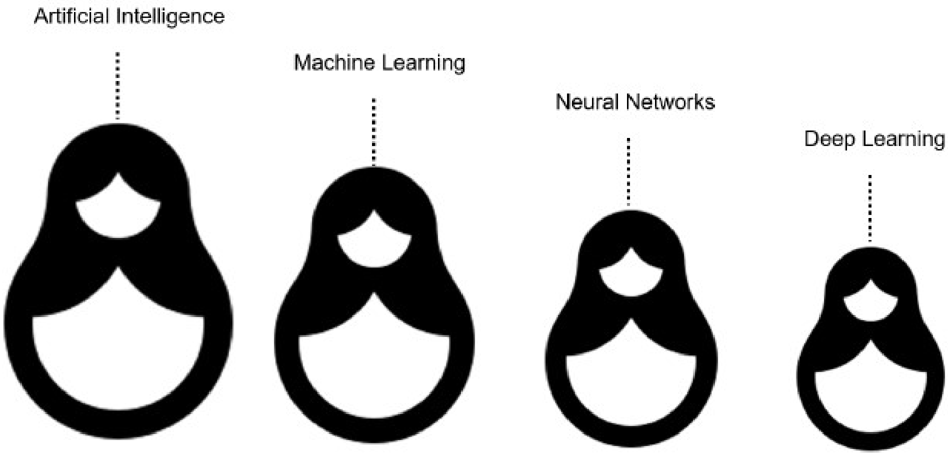

Figure 3 - Relationship Between AI, ML, ANN, and DL (IBM, 2020c)

By applying these technologies, an ET system could learn what sensor metric trends to associate with particular outcomes, and be able to flag probable fault occurrences; diagnose fault causes; instinctively self-heal a problem; and where possible, automatically prevent faults from occurring at all (Brookshear & Brylow, 2018; Ericsson, 2021a; Forbes, 2019). This would decrease resource requirements, improve efficiency, and cut costs (Ericsson, N.D.a). Additionally, to maintain sustainability, vendor support, and improve investor sentiments, it would be advisable that the ET technology forecasting and implementation department engages with available vendors to align themselves with the latest available and reliable technology trends (United Nations, 2019; International Telecommunications Union, 2018).

In-Depth Solution Review:

1.) Implementation Plan and General Solution Concerns

Unfortunately, because the technology application in this case is incredibly specialised, a turn-key product with its associated benefits would be hard to come by, and a lot of onsite research and testing will be required (Investopedia, 2020). Therefore, it is crucial to collate all information pertaining to the current ET technology philosophy, network topology, infrastructure installed, security policies, internal support mechanisms and skills, as well as the various equipment vendors used, before hastily applying the new promising technology (Brookshear & Brylow, 2018; Eid, 2015; Ghallab, 2019). Furthermore, understanding that it may take time to research a holistic and thorough solution, moreover, to build a sufficient and well-structured database, and use that to train an ET focussed ML system, it would be advisable to implement the solution in phases with accompanying testing cycles (Brookshear & Brylow, 2018; University of Essex Online, 2021b). In this approach the initial implementation would hand little, to no control and access rights over to the system, but increasingly give some form of such over time and the relevant phases (Brookshear & Brylow, 2018; Gillis, N.D). This would minimise any negative impacts and provide sufficient time to respond to issues that may arise (Brookshear & Brylow, 2018; Gillis, N.D). Therefore, the appropriate Software Development Life Cycle (SDLC) and project implementation models would need to be selected to accommodate the mission critical environment (Brookshear & Brylow, 2018; Gillis, N.D). Additionally, it would be important to ensure staff are correctly trained to handle the new technology before full implementation, which would provide the necessary specialised knowledge and may maintain job security (Brookshear & Brylow, 2018). This however may be a challenge as the software development environment associated with AI requires a highly specialised skillset not part of the current ET skills base.

Technically, the goal would be a solution which has seamless interoperability across the various equipment platforms communicating with the central Agent program, which may present a challenge due to the multi-vendor environment inherent in ET (Ericsson, N.D.b). However, sensors already existent in the network in the form of localised equipment sensors and meters, may be used to directly feed data into the Agent program replacing the current NMSs (Brookshear & Brylow, 2018). The possibility of direct-sensor-feeding is a lot higher if the related equipment uses the Simple Network Management Protocol (SNMP) as the interface protocol between equipment sensors and the current NMS (Microsoft, 2018). If the relevant data cannot be accessed directly through an open standard protocol like SNMP, it is possible that it could be sourced from the current individual NMSs relating to specific equipment OEMs, via an Application Programming Interface (API) applicable to each software unit (IBM, 2013). Essentially, sourcing the correct accurate data and building the required database relevant to the ML system will be one of the greatest challenges, especially considering the various hardware and software system facets being reported on by sensors (Ericsson, 2021a)

Although there is still a lot of hype around AI's applications, especially in the realms of the never-before-seen General AI system, there are real-world solutions in the field of concern (IBM, 2020). Therefore, it may be necessary to engage and collaborate with a specific supplier, or various vendors to produce an ultimate solution which is tailored to the specific environment (Brookshear & Brylow, 2018).

2.) Social and Ethical Implications

Whenever a disruptive technology like ML is adopted, there are various social and ethical implications (Ghallab, 2019). In the current case study, one major social implication is the fact that certain jobs are likely to become redundant as they would be replaced by the intelligent computer system (Bossman, 2016). However, as previously mentioned, should ET upskill staff appropriately this may not be the case (Indeed, 2021). In terms of benefits, by providing the network with fault predetermination there would be less risk of failures which would negatively affect society, especially considering the critical role Eskom plays in terms of producing the electricity which is used to run the economy, and ensure daily living needs like heating, lighting, and water can be provided (Forbes, 2019).

Ethically, because the data trends analysed are specifically related to equipment-generated information there is no Personally Identifiable Information (PII) that is being stored or analysed (Ghallab, 2019). Essentially, portion of the database used to train the ML system and make live decisions, is only a form of metadata pertaining to data movement, rather than data itself (Brookshear & Brylow, 2018). One may argue that trends associated with data movement patterns are still an infringement upon personal privacy, but again the “metadata” is very restrictive in terms of such analysis (Brookshear & Brylow, 2018). The type of analysis that would be able to breach ethical mandates as set forth by various organisations, would require much more information granularity, and data depth in terms of the OSI Reference Model and the associated applications to link particular trends to specific data sources (Cisco, 2005). Additionally, because the data being transported by the ET network is of a Unified Communications (UC) nature, it would be even more difficult to associate data patterns specifically to equipment or people (Cisco, 2005).

3.) Possible Security Threats

To ascertain the relevant security threats a holistic risk assessment would need to be performed (Nieles et al.,2017). However, if we consider Confidentiality, Integrity, and Availability, known as the CIA triad of security, a few preliminary observations are possible (Nieles et al.,2017). Beginning with availability, it is essential that the ML system not make any incorrect decisions or flag errored performance statistics, as this will certainly cause loss of availability to information and services. Furthermore, system redundancy is essential to ensure any loss of the main system does not impact the business negatively (Nieles et al.,2017). Additionally, only a very low error tolerance would be allowed considering the large-scale impact incorrect decision-making or reporting may cause (Nieles et al.,2017). Confidentiality has already been touched on in the previous section in the form of personal data security. Integrity is another area of concern, as any incorrect data fed to the ML system would cause incorrect data output (Bossmann, 2016). Therefore, there may need to be some form of software filter to error-test the data before providing the ML software system noisy data inputs (Gupta & Gupta, 2019). In terms of additional attack vectors relating to external threat actors gaining access to the critical system, there will be no foreseeable change to any current infrastructure setup (Nieles et al.,2017). Therefore, the normal firewalls and security measures must be adapted to allow any new Transmission Control Protocol (TCP) or User Datagram Protocol (UDP) ports required by the ML system for access (Fortinet, N.D). An advantageous aspect of the ML system is that it could be trained to perform functions of an Intrusion Prevention System (IPS), extending security to all equipment holistically, and increasing overall security performance (Ericsson, 2020).

Conclusion

In conclusion, a ML solution using DL is very promising in terms of achieving the desired goal of an AI system which can predetermine faults, analyse existing faults, and mitigate fault impact in the ET environment (Cisco, N.D.b; Ericsson, 2018). The benefits will definitely outweigh the disadvantages, and the disadvantages can be mitigated through a well-planned mitigation strategy in line with a holistic risk assessment (Allen & Darrel, 2018). However, there are various challenges to getting the desired solution implemented, making a turn-key product unattainable (Ghallab, 2019). Therefore, it will be required that various on-site research and development be done, and that collaboration with various equipment vendors take place (Gillis, N.D). Special attention will need to be placed on the formation of the required database, as well as the fact that the environment allows very little decision-error tolerances because of its mission critical nature (Gupta & Gupta, 2019).

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