Multi-Agent Model-Based Optimization for Future Electrical Grids

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Proefschrift

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Summary

The electricity grid is one of the most complex systems created by human beings. It consists of an intricate network of components such as generators, transmission and distribution lines, transformers, breakers, various controllers, and various measurement and monitoring systems. The grid has been going through significant changes in past decades with new technological developments, deregulation, distributed generation, smart grid, and asset management. A synergy of these new developments has contributed to a better grid by improving its reliability and performance. However, the efficient coordination between various components of the grid and various new developments has been a constant challenge. For instance, new components that are introduced in the grid often have state of the art measurement and monitoring systems whereas the aging components have limited measurement and monitoring systems. We need to maintain the balance between these new and old technologies such that the new developments should be exploited to their full extent and the old systems should be reinforced such that their operational life could be extended without affecting their reliability significantly.

Due to the complexity of the grid control, a centralized control of every component and every aspect of the grid is practically impossible. A distributed control system provides the ability to simplify the complexity of the grid control problem while solving the complex problem of coordination between its sub-systems. A distributed system is modular in nature and this system could be introduced to the grid in incremental phases within large networks. Multi-agent control can be used in the grid to realize a distributed system. Using agent theory, a concept of an intelligent component is described in this thesis. The intelligent component has the ability to make intelligent decisions based on the state of the component.

With developments in measurement and monitoring technologies, we are better informed of the state of the grid components. By using these systems, we have the ability to better predict the health state of the grid components. There has also been significant developments in understanding how the health state of the grid components evolves over their lifetime. A model of the health state coupled with the new measurement and monitoring system allows us to predict the health state of the system. A framework of model-based optimization is included in the intelligent component. This framework consists of a predictive health model. An optimization is performed based on the prediction of the health model and the control decision of the intelligent component is made on the basis of this optimization.

In order to solve the whole problem of the electricity grid, the intelligent components need to collaborate within each other. A concept of an intelligent network is also proposed in this thesis. In the intelligent network concept, a hierarchical structure of intelligent components has been developed. In order to optimize their global performance, the intelligent components need to collaborate with each other. The intelligent components within this hierarchical structure coordinate by exchanging their local states and their future plans.

Coordination within intelligent network is only possible if all their intelligent components can communicate effectively. For this, an information interface was developed. The interface is particularly of importance in the electricity grid as different control systems used within the grid are often developed by different vendors. Common Information Model (CIM) has been deployed in the grid for network control, data exchange, and energy management systems. This CIM is further developed in this thesis so that it can accommodate the concept of the intelligent component and the intelligent network developed in this thesis.

A case study of dynamic loading of transformers is used to illustrate the concept. The example is used throughout the thesis to demonstrate applicability of concepts of the intelligent component, the intelligent networks and the information interface.

A dynamic loading scheme of transformer is developed based on the concept of intelligent components. A predictive health model for the top-oil temperature and the hot-spot temperature is developed. The predictive heath model predicts the top-oil temperature and the hot-spot temperature based on the loading of the transformer. An optimization method is developed which gives the dynamic rating of the transformer based on these predictions. The dynamic loading (DL) agent, developed here, could make local decisions on its dynamic rating based on the predicted loading of the transformer.

This dynamic loading is applied in a electricity grid to illustrate the concept of intelligent networks. Multiple transformers within the grid have their own dynamic loading agents. An optimal power flow (OPF) agent is developed which controls the grid based on an optimal power flow algorithm. The OPF agent obtains the dynamic ratings from the dynamic loading agents of the transformers. Based on these dynamic ratings, the OPF agent controls the power flow of the grid. The OPF agent also sends predicted loadings of the transformers to its DL agents. These predicted loading is used by the dynamic loading agents which use this information for the next time step.

The information interface is also described for this intelligent network implementation. In order to communicate dynamic ratings and predicted loadings of transformers, an extension to the CIM is developed. The workflow of the intelligent agent and its interaction with the extended CIM is also demonstrated.

It is concluded that the use of the predictive health model enables the optimization for the future prediction horizon. The intelligent component concept is modular in nature which is useful for the electricity grid. The intelligent network concept effectively combines intelligent components within it. The framework developed in this thesis is also demonstrated with examples of dynamic loading of transformers within an electricity network in which the loading of the transformers are increased by 50 % of its nominal rating.

Possible future extension of the predictive health model to include other electrical components models such as cables, circuit breakers, and generators, etc. is also discussed. A suggestion on the implementation phases of the concept developed in this thesis is also presented. It is suggested that the concept would be practical to be implemented in gradual phases to the electricity grid. New developments are also a potential opportunity for the implementation of the concept as the marginal cost is minimal for introducing the concept.

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Samenvatting

Het elektriciteitsnet is één van de meeste complexe systemen dat door de mensheid gecreerd is. Het bestaat uit een ingewikkeld netwerk van generatoren, transmissie- en distributielijn, transformatoren, stroomonderbrekers, controllers en verschilende soorten meet- en monitoringsystemen. Het net heeft in de afgelopen decennia verschillende significante veranderingen ondergaan met nieuwe technologische ontwikkelingen zoals gedistribueerde opwekking, smart grids en zaken zoals deregulatie en asset management. Een synergie van deze nieuwe ontwikkelingen heeft middels het verbeteren van de betrouwbaarheid en de prestaties bijgedragen aan een beter net.

Echter, een efficiente coordinatie tussen de verscheidene componenten in het net en de nieuwe ontwikkelingen is altijd een constante uitdaging gebleken. Een voorbeeld is dat nieuwe componenten in het net vaak beschikken over de nieuwste meet- en monitoringsystemen terwijl juist de verouderde componenten niet of nauwelijks beschikken over deze systemen. Het is daarom noodzakelijk om een balans te vinden tussen nieuwe en oude technologieen zodanig dat de nieuwe systemen ten volle gebruikt kunnen worden en de oude systemen voldoende versterkt worden dat de operationele levensduur verlengd wordt zonder dat de betrouwbaarheid in het geding komt.

Vanwege de complexiteit van het netbeheer is een gecentraliseerd beheer van elk component en elk aspect van het net praktisch onmogelijk. Een gedistribueerd controlesysteem biedt de mogelijkheid om de complexiteit van het netbeheersvraagstuk te reduceren door coordinatie tussen de netcompononent of subsystemen. Een gedistribueerd systeem is modulair en zou in oplopende fases geintroduceerd kunnen worden in grote netwerken. Het concept van multi-agent control zou gebruikt kunnen worden om een dergelijke gedistribueerd systeem te realiseren. In dit proefschrift wordt de theorie van agenten gebruikt om het concept van een intelligente component uit te werken. Een intelligente component heeft de mogelijkheid om beslissingen te nemen op basis van de toestand van de component.

Met de ontwikkelingen op het gebied van meet- en monitoringsystemen zijn we in principe beter in staat om de gezondheidstoestand (health state) van de netcomponent te bepalen. Met deze systemen zouden we ook beter in staat om de toestand te voorspellen voor een bepaalde tijdshorizon. Er is ook significante vooruitgang geboekt in het inzicht hoe de toestand van netcomponenten zich ontwikkelt gedurende de levensduur. Een model van de toestand gekoppeld met de nieuwe meet- en monitoringsystemen stelt ons in staat om de toestand van het gehele systeem te bepalen. Een framework van modelgebaseerde optimalisatie is ingebed in een intelligente component. Dit framework bestaat onder andere uit een predictive health model. Een optimalisatie wordt uitgevoerd op basis van de voorspellingen van het model en op basis van deze optimalisatie worden de bestuursbesluiten van het

intelligente componenten genomen.

Om de problematiek van het steeds complexer wordende elektriciteitsnet aan te pakken, moeten de intelligente componenten ook met elkaar samenwerken. In dit proefschrift wordt een concept voor een intelligent netwerk voorgesteld. In dit concept wordt een een hierarchische structuur van intelligente componenten ontwikkeld. Om de algehele prestaties te optimaliseren moeten de intelligente componenten dus met elkaar samenwerken. Dit doen de componenten binnen deze structuur door informatie over hun huidige health states en toekomstige plannen met elkaar uit te wisselen.

Bovengenoemd soort coordinatie binnen een intelligent netwerk is alleen mogelijk als alle componenten binnen dit netwerk in staat zijn om effectief met elkaar te communiceren. Hiervoor is een interface voor informatieoverdracht ontwikkeld. Deze interface is zeker van belang in elektriciteitsnetwerken omdat hier verschillende controlsystemen gebruikt worden die vaak door verschillende fabrikanten geproduceerd zijn. Voor dit doel van netbeheer, data-uitwisseling en energie-management bestaat reeds het Common Information Model (CIM). In dit proefschrift is dit bestaande CIM verder uitgebreid zodat het overweg kan met intelligente netwerken en componenten.

In dit proefschrift wordt een case uitgewerkt met het dynamisch belasten van transformatoren om het concept van predictive health management te illustreren. Deze case zal door het hele proefschrift gebruikt worden om de concepten van intelligente componenten, netwerken en de uitbreiding van het CIM verder concreet uit te werken.

Een blauwdruk voor het dynamisch belasten van transformatoren is ontwikkeld op basis van intelligente componenten. Voor de top-oil temperatuur en de hot-spot temperatuur is een predictive health model ontwikkeld waarmee deze temperaturen worden voorspeld op basis van de belasting van de transformator. Hiermee is een optimalisatie-methode ontwikkeld waarmee op basis van deze voorspellingen een dynamische waardering wordt afgegeven. Het hierboven beschreven blauwdruk kan worden beschouwd als een agent, in dit geval een dynamic loading (DL) agent. Deze agent kan noodzakelijke beslissingen nemen op basis van deze dynamische waarderingen.

Dit proces van dynamisch belasten is toegepast op een simulatie van een elektriciteitsnet om het concept van intelligente netwerken te illustreren. Meerdere transformatoren binnen een net zijn elk uitgerust met een dynamic loading agent. Een optimal power flow (OPF) agent is ontwikkeld die het net bestuurt op basis van een algoritme voor optimale vermogensstromen. De OPF-agent ontvangt de dynamische waarderingen van elke DL-agent. Op basis van deze waarderingen zal de OPF-agent de vermogensstromen bijsturen. De OPF-agent zal ook de voorspelde belastingen van elk van de transformatoren sturen naar alle DL-agenten die deze infomatie weer gebruiken voor de volgende tijdstap.

De informatie-interface benodigd voor bovenstaande case wordt ook beschreven. Om ervoor te zorgen dat de dynamische waarderingen en voorspelde belastingen van de transformatoren worden uitgewisseld, is een uitbreiding van het CIM ontwikkeld. Het werkschema van de intelligente agent en de interactie ervan met de uitgebreide CIM wordt gedemonstreerd. Er wordt geconcludeerd dat het gebruik van predictive health management de mogelijkheid biedt om te kunnen optimaliseren voor een toekomstige tijdshorizon. Het concept van intelligente componenten is modulair waardoor het bruikbaar is in het elektriciteitsnet. Verder is aangetoond dat het concept van intelligent netwerken ervoor zorgt dat daarmee alle componenten binnen een dergelijk intelligent netwerk op een effectieve manier met elkaar samenwerken. Het in dit proefschrift ontwikkelde framework wordt ook gedemonstreerd met voorbeelden zoals het dynamisch belasten van transformatoren waarbij de belasting van de transformatoren verhoogd werd met 50 % boven de nominale rating.

Mogelijke uitbreidingen van het predictive health management in de toekomst kunnen zich richten op andere elektrische componenten zoals kabels, onderbrekers, en generatoren, etc.

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Contents

Chapter 1

Introduction

Electrical energy has become one of the basic necessities of our world. It is the most convenient form of energy available to us because of ease of transportation and transformation. Electricity grids are one of the most complicated systems to control ever developed by human beings to transport and distribute electrical energy. These grids have been continuously evolving for the past century. The building blocks of these grids, such as transformers, cable, circuit breakers, etc., have to keep up with this change. These electrical infrastructures should become intelligent so that they can keep pace with these changes without compromising the reliability of the grids.

1.1 Future electricity grids

Electricity grids have been developing over the decades, to become a complex network of transmission and distribution systems between power generators and power consumers. The main goal of electrical grids is to provide reliable electrical energy at an acceptable power quality to consumers with an optimal cost. In order to fulfill this goal, the grid should be managed in an effective way. The functionalities that have to be managed can be categorized into three divisions, namely operational, maintenance, and planning management. The time scale of these three managements vary, with operational managements having the shortest time scale and the planning management having the longest time scale [1]. The categories and typical time scales are indicated in Figure 1.1. Some of the key functionalities of operational, maintenance, and planning management are also listed in the figure.

Recently, electrical grids are undergoing tremendous changes because of following factors:

- **Deregulations** have changed the power industry from the traditional state owned utility structure into a group of independent companies involved in generation, transmission, and distribution. Not only the structure of the industry has been changed, but also the way of financing generation, transmission, and distribution also has been changed. Service oriented stated owned utilities have been replaced by an investment oriented approach of power companies [2].

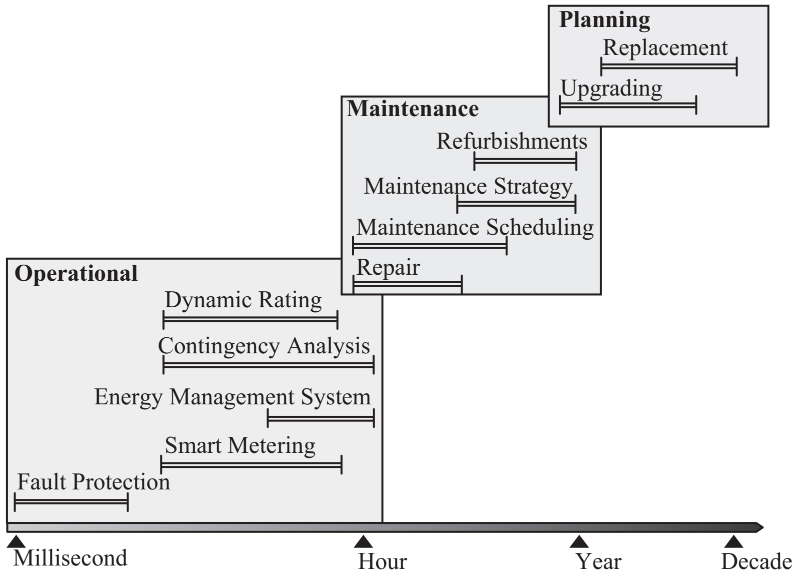

Figure 1.1: Functionalities of electricity grid categorized with respect to time into operational, maintenance, and planning management. The time scale of the management varies from milliseconds to hours for operational management. For planning management, this time scale spans from years to decades.

- A significant portion of the electrical infrastructure is reaching the end of its operational age within the coming few decades [3]. On the one hand, the impending replacement wave of these **aging infrastructures** will require extensive investments in the near future. On the other hand, the aging infrastructures are degrading the reliability of the system. There is a greater need for reducing the risk of aging related failures and at the same time deferring the new investment by extending the life of the aging infrastructures.

- Because of environmental and societal concerns, the trend has shifted towards sustainable power generation. **Renewable energy sources**, such as wind power and solar power are intermittent in nature. This causes greater variation of power flow in the network. Power electronics used in the renewable energy sources generate repetitive transients. These repetitive transients accelerate the aging of the components of the grid [4]. In order to effectively use the energy from these renewal energy sources, optimal use of the electricity network and the electric loads is thus required.

1.2 Asset management in future grids

Electrical utilities are asset intensive organizations with numerous electrical infrastructures. Deregulation of the power industry has compelled utilities to maximize the performance of their assets with a minimum expenditure [1]. Asset management is required for the optimization of the usage of assets considering all performance, cost, and risk constraints [5].

The goal of asset management is to balance the performance of the asset to the expectation of the stakeholders [6]. The performance of assets is indicated in terms of the reliability and the power quality. The stakeholders include asset owners, regulators, employees, and consumers. They each have their respective expectations from the asset and the system.

According to [6], asset management of electrical grids has three main aspects, namely technical, economical, and societal.

- **Technical aspects** include technical performances of the assets such as the failure rate, the degradation, and the remaining life of the equipment. Different condition monitoring systems, which can track the aging, have been developed for different types of equipment.

- **Economical aspects** include the cost of the equipment and the cost of maintenance and operation of the equipment.

- **Societal aspects** refer to the preferences of the society. Societal aspects include environmental concerns, issues of aesthetics, reliability of the power delivered, and welfare of the society.

These aspects should be considered during the asset management process to deliver reliable power which is also economical, technically feasible, and socially acceptable.

The reliability of the grid can be improved by monitoring the condition of equipment and by taking preventive actions based on this condition [2]. Presently, the use of condition monitoring and diagnostics information is limited to the maintenance management. With the increase in number of aging infrastructures, stringent criteria to maintain the reliability of the electricity grid, and advancements in condition monitoring techniques, the condition information should be used for operational, maintenance, and planning decisions. The use of the condition information for different functionalities of operational, maintenance, and planning decisions is presented in Figure 1.2.

The condition information can be used to estimate the state of the aging process of the equipment. This state of the aging process is defined as the health state of the equipment. The rate of the aging process depends on various stresses which are applied to the equipment. Thus, the health state of the equipment is given by the accumulation of these stresses.

This health state can be used in the contingency analysis of the network which analyzes the reliability of the system in the case of probable faults. Utilization of the equipment according to its health state can be achieved by dynamic rating of the equipment in which its loadability is changed dynamically with time. Optimization of the maintenance and the planning management can be achieved by predicting the impact of the management actions on the health state of the equipment. The management of electrical infrastructures is based on condition monitoring and diagnostics information. With the information of the condition of electrical infrastructures, an optimal use of electrical infrastructures at a minimal cost could be possible.

In order to integrate the condition parameters in the asset management of the electricity grid, the following components have to be developed:

- Models that describe the aging of equipment

- Monitoring and diagnostics systems for determining the condition of equipment

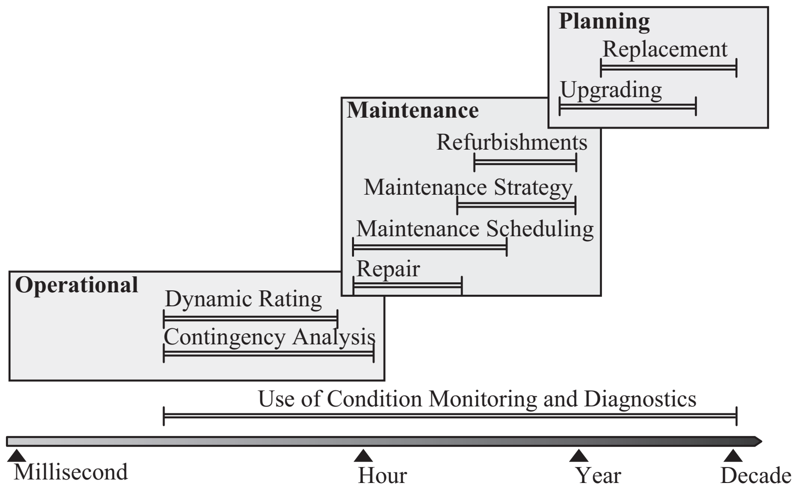

Figure 1.2: Use of condition monitoring and diagnostics off assets in asset management. The condition information should be used in operational, maintenance, and planning managements.

- Models of the condition assessment of equipment
- Methods for optimization of operational, maintenance, and planning management based on the condition data
- Collaboration methods between different equipment and management systems for improving the condition assessment and the optimization of their management actions.

1.3 Operational management of future grids

Traditionally, the generators primarily consisted of large power generators which were connected to the transmission systems and the consumers were connected to the distribution networks. The power flow from the generators to the consumers was unidirectional from the transmission to the distribution systems. Generators of renewable energy sources are decentralized in the grid as these dispersed sources are often connected to the distribution networks. Due to introduction of the distributed generation in the distribution networks, the power flow in the electricity grid has been changing. The distributed generations give rise to bi-directional flow of the power between the transmission systems and the distribution systems [7].

The energy generation from renewable sources is often intermittent and does not match with the demand of the energy. In order to maximize the use of the renewable energy, control of the consumer load is required. The concept of the smart grid has been evolving to address the mismatch [8]. In the smart grid, the demand of the consumers is managed according to the generation. For instance, during excess generation, the energy can be stored in various systems, such as batteries, flywheels, compressed air systems, combined heat and power (CHP) generators, etc. Electrical vehicles have been going through significant developments

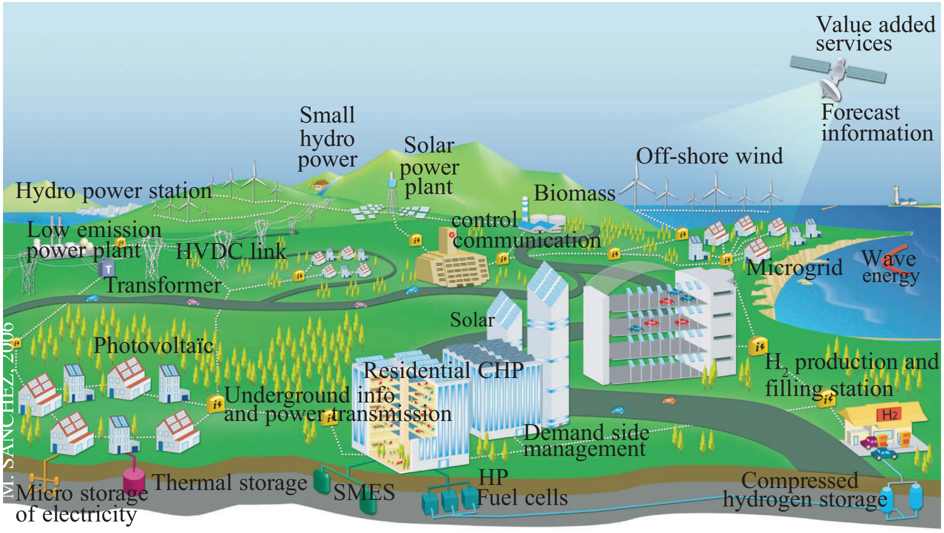

Figure 1.3: Concept of a smart grid in the future network according to the European SmartGrids Platform [8]. The smart grid has distributed renewable sources (such as wind, solar, hydro, etc.), increased communication capabilities, and advanced equipment (such as HVDC, energy storage, etc.).

and their use has been increasing with the advancement in their performance. The battery storage of these vehicles could also be used as distributed storages [9]. The power stored in these systems can be discharged to the system in the case of a reduction of the generation. The power consumption by low priority loads, such as refrigerators, air conditioners, etc., can also be reduced in such case. A schematic of the concept of the smart grid in a future grid, envisioned by European SmartGrids Technology Platform [8], is illustrated in Figure 1.3.

The bi-directional power flow and the control of the consumer demand both result in greater fluctuations of the power flow in the transmission and distribution systems. The loading capacity of components such as transformers, cables, or overhead lines in the transmission and distribution systems is determined by the assumption of the constant loading. The loading capability of the component is primarily constrained by the thermal characteristics of the materials used in the component. The thermal state of the component can be monitored with different temperature sensors within the component and can also be estimated based on the operating condition of the equipment. Based on the thermal state of the component, dynamic rating of the component is possible. The dynamic rating of the components ensures their optimal utilization. The power transfer capability gained by the use of the dynamic rating could defer the investments required for upgrading of the components.

Aging of the components reduces their reliability [10]. The operational age of these components can be extended if their reliability could be maintained within the acceptable level. Monitoring the health state of the equipment and performing the required maintenance based on the health assessment can improve the reliability of the aging components. Dynamic rating of the component based on the health state will ensure the optimal use of the equipment without accelerating the deterioration of its health state. A model of the degradation of the component's health state along with the monitoring and diagnostics is required to predict the effect of the dynamic loading. The optimal loading of the component can be determined by evaluating the prediction of the health state for different possible scenarios.

1.4 SINERGIE project

SINERGIE stands for "synergie van intelligentie en energie - in elektriciteitsnetten van de toekomst" in Dutch, which translates to English as "synergy of intelligence and energy - in electricity grids of the future". SINERGIE project is funded by the EOS (Energie, Onderzoek, en Strategie) funding program.

This project focuses on the electricity grids of the future with special emphasis on maintenance and management in the changed context of the future grid. The objectives of the project are summarized as follows [11]:

- Integrate the energy and diagnostic technology effectively.
- Data-reduction and analysis coming from different continuous monitoring systems has to be investigated in order to show only the relevant information.
- Adjust currently available models to predict the remaining lifetime of high-voltage assets under new fluctuating load profiles.
- Install diagnostic tools in different high-voltage assets to assess their condition and develop a prototype of condition based asset management tool.

In order to achieve above mentioned objectives, five work packages are developed. The structure of work packages and interaction between them are shown in Figure 1.4. The arrows in the figure define knowledge flows between work packages. Descriptions of the work packages (WP) are as follows [11]:

- **WP 01 Architecture:** defines information architecture and information flow between intelligent components for management of electrical infrastructure.
- **WP 02 Supporting processes:** defines support processes for providing integral (technical, economical, and societal) value of high-voltage assets.
- **WP 03 Intelligent components:** defines autonomic components which make decisions based on the local condition information and the coordination with other components.
- **WP 04 Methods, techniques, and models:** defines assessment of the remaining life of components and determination of the policy to use new materials.
- **WP 05 Effects changing environment:** defines influence of changing operational conditions on components of future power system.

The research presented in this thesis deals with the first three work packages. The requirements and goals of this research are presented in following sections.

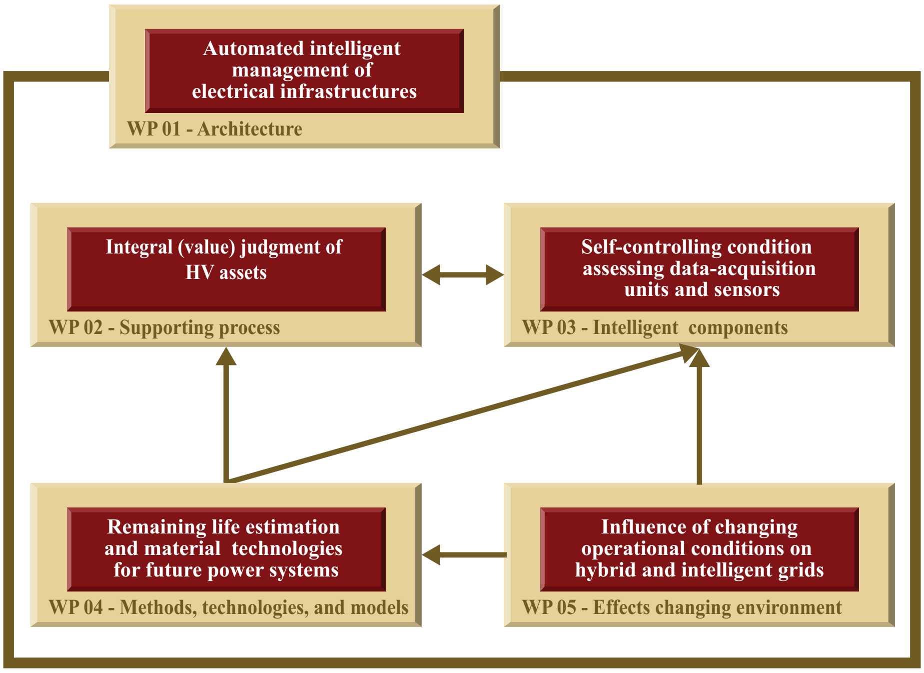

Figure 1.4: Five work packages of SINERGIE project [11]. The arrows define the knowledge flow among work packages.

1.5 Requirements of future grids

Future grids should be able to deal with the aging electrical infrastructures on the one hand and changes in the operation of the grid due to distributed generation on the other hand. The grids should be able to extend the operating life of the aging infrastructure considering its changing operational conditions. The flexibility and controllability offered by the distributed generation together with the development of new technologies and equipment should be exploited for optimal usage of the electrical infrastructures. The requirements of the future grids can be given as follows:

- Life extension of the aging equipment without degrading the reliability of the grid.
- Monitoring and prediction of the health state of the critical components in the grid.
- Usage (loading) of the equipment based on the predicted health state and the predicted demand.
- Coordination of the usage of different equipment in the network.

1.6 Goals of this research

In order to fulfill the requirement of future grids, an intelligent system needs to be developed. This intelligent system should take into account the aging infrastructures which have to work with changing operating conditions. The coordination of different equipment within the network should also be taken into account. The goals of this research are summarized as follows:

- Develop a framework for modeling the health state of electrical equipment.
- Develop an intelligent component which uses the model to optimize the usage and maintenance actions of equipment.
- Coordinate intelligent components to manage the electrical network.
- Define information exchange between intelligent components in order to achieve the collaboration.

The scientific goals of this research are summarized as follows:

- The framework should be distributed in nature.
- The distributed system should be flexible in nature with regard to incorporation of future improvements.

1.7 Organization of this thesis

This thesis presents a model-based optimization framework for management of future electricity grids. The outline of this thesis is as follows:

- **Chapter 2:** This chapter introduces the background of concepts used in the thesis. The concept of a model-based optimization is presented in this chapter. The model-based optimization can be used in a distributed approach by using a multi-agent system. The description of the multi-agent system used in this thesis is presented in this chapter.

- **Chapter 3:** The concept of an intelligent component is developed in this chapter. A framework of model-based optimization is proposed for this intelligent component. The framework uses a predictive health model. This intelligent component solves a particular local problem of equipment using this framework. In order to solve the global optimization problem, a distributed approach based on a hierarchical structure of intelligent components is discussed in this chapter. The concept of intelligent components is implemented for the dynamic loading of a transformer in this chapter.

- **Chapter 4:** An intelligent network which consists of a set of distributed intelligent components is presented. The distributed architecture of the components within the intelligent network is proposed. The coordination of components within the intelligent network is also explained. An example of the transformer loading control in the IEEE 14 bus network is implemented, using the concept of the intelligent network. A comparison of the distributed approach using the intelligent network and the centralized optimization approach is also performed in this chapter.

- **Chapter 5:** In order to solve the global problem of an intelligent network, intelligent components within the intelligent network need to communicate with each other. The information interface between these intelligent components is presented in this chapter. The Common Information Model (CIM) has been used increasingly for information exchange in the grid. This CIM is extended in this chapter to include the collaboration of intelligent components. The developed CIM extension is illustrated for the information exchange of the load control of transformers in IEEE 14 bus network.

- **Chapter 6:** Conclusions of this research are summarized in this chapter. Possible future research works are also discussed.

Chapter 2

Intelligent grid concepts

A plethora of intelligent systems has been developed and implemented for electrical grids [12]. Different systems address problems of different fields such as load flow, load forecasting, protection, dispersed generation, power system dynamics, international power markets, etc. This chapter focuses on the background of the intelligent grid concept used in this thesis. An intelligent model-based management of electrical grids based on the condition information of the asset is presented in this chapter.

An introduction of intelligent systems in the electricity grid is presented in Section 2.1. Knowledge-based systems are extensively used in condition estimation and maintenance of electricity grids [6], which is described in Section 2.2. These systems are based on the expert knowledge, which is difficult to extract and to implement. To overcome this difficulty, a model-based control system for electricity grids is proposed in Section 2.3. This control system can be incorporated in agents. The concept of agents and its application in the proposed model-based control system is discussed in Section 2.4. By using an agent in corporation with the model-based control system, a distributed agent system can be developed. By using the distributed approach, a complex problem can be divided into sub problems which are easier to solve. In Section 2.5, the distributed approach for the management of electricity grids is presented which uses the proposed model-based control system with intelligent agents. The conclusions of the chapter are included in Section 2.6.

Parts of this chapter have been published in [13] and [14].

2.1 Introduction

As mentioned in Chapter 1, electricity grids have been changing over the last decades. Notably, there is a need for incorporating changes in the operational management of the grids due to the introduction of distributed generation. The aging infrastructures of the grids should be managed such that they are operated optimally and the maximum utilization of the distributed generation is achieved. In addition, the aging equipment should be managed and operated according to the condition of the equipment.

Due to advancements in measurement techniques and sensor technologies, a significantly higher amount of technical information about the equipment of the grid has become available. Various online and offline condition monitoring systems have been developed for different types of equipments, which determines the condition of the equipment. The condition information can be used in the asset management in order to manage and operate the equipment optimally.

The condition information generated by the equipment should be translated to the health state of the equipment. The health state can then be utilized to optimize operation, maintenance, and planning management. Currently, the condition information is only used by knowledge-based systems for the maintenance management.

2.2 Knowledge-based systems in electricity grids

Maintenance of equipment in the electricity grid is one of the important factors for maintaining the reliability of the grid. Maintenance strategies implemented in electrical equipment can be categorized into three types [2], [15]:

1. **Corrective Maintenance:** Maintenance is performed only after breakdown of the equipment.

2. **Time-Based Maintenance:** Maintenance is performed at predefined/fixed time steps.

3. **Condition-Based Maintenance:** Maintenance is based on the condition of the equipment.

Condition-based maintenance is becoming more popular in electrical infrastructures, compared to the traditional time-based maintenance [2]. Condition-based maintenance reduces cost by performing maintenance only when it is needed. Online and offline condition monitoring systems can be used to assess the condition of the equipment.

Knowledge rules and standards are used for the condition-based maintenance [6]. The knowledge rules and standards are based on the expert knowledge and/or the analysis of the performance statistics of a set of similar equipment. The effectiveness of the knowledge-based system depends on the accuracy of the expert knowledge. In addition, the changes in the operational condition of the equipment in the future grids could be difficult to be translated into the expert system.

The evolution of the condition of the equipment is a dynamic process which depends on its usage, maintenance actions, and environmental conditions. Increasing the loading of equipments tends to deteriorate their condition more rapidly. With the operational information of the equipment, the evolution of its condition can be accurately predicted. Conversely, equipment with an inferior condition can be loaded lightly in order to increase its life expectancy and reliability. Incorporating the operational regime of the equipment in the expert system would require complex knowledge rules which might become unmanageable in a large electricity grid. Thus, the dynamics of the evolution of the condition of the equipment should be investigated, so that its future trend can be predicted. The condition of the equipment depends to a great extent on its operation. A model-based control system for predicting the evolution of the condition is required, which is presented in the next section.

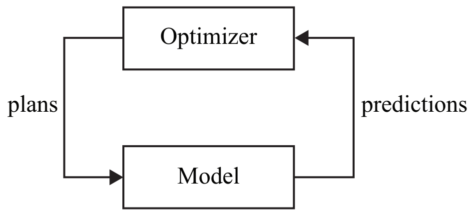

Figure 2.1: Model-based optimization. The model generates predictions based on the plans. The optimizer uses the model to evaluate effects of different possible plans. The optimizer generates an optimal plan based on these predictions.

2.3 Model-based control systems

In model-based control systems [16], a mathematical model of a system of interest, which replicates its behavior, is developed. In our case, a model of the dynamics of the health state of equipment is considered. This model is able to simulate and/or predict effects of different scenarios in which different control actions, such as maintenance actions, loading of the equipment, are employed.

The model-based control system uses a model of the system and an optimizer as shown in Figure 2.1. The optimizer generates possible future plans, which are sent to the model. The model predicts the effects of these plans. The optimizer evaluates the effects and searches for the optimal control actions, which gives an optimal predicted future response.

A prediction horizon of a certain time in the future can be taken into account for determining the optimal control actions. Thus the anticipated impacts of future actions are also considered by predicting of their future responses. In addition, the dynamics of the system is taken into consideration by using the model of the system. The predictions of the model for given actions are close to the actual responses, provided that the system is accurately modeled. In such a case, the validity of the optimal solution is improved, compared to knowledge-based systems. Knowledge-based systems tends to be based on a complex set of expert reasoning which is difficult to implement and prone to errors in the process of implementation. Thus, the implementation of the model-based control system is simpler in comparison with a knowledge-based system. The critical part of the model-based control system is the model of the system, which can be validated by comparing the simulation results and measurements from the real system.

2.3.1 Concept of model predictive control

Model-based control systems have been implemented in various systems, such as process control systems, transportation management, and water flow control systems [12]. Model predictive control (MPC) is one of the model-based control methods applied in process control applications [17] and power systems applications [16].

MPC can be defined as an optimization problem. An optimization problem consists of a cost function which has to be minimized (or maximized). The optimization process should follow the constraints of the system. These constraints can be a mixture of equality constraints and non-equality constraints. In MPC, the model of the system is included in these constraints. A generic optimization problem of MPC is defined as follows:

$$\min_{\mathbf{u}(k),\cdots,\mathbf{u}(k+N-1)} \sum_{l=0}^{N-1} J\left(\mathbf{u}(k+l),\mathbf{x}(k+l),\mathbf{y}(k+l)\right), \tag{2.1}$$

subject to

$$\begin{aligned}
\mathbf{x}(k+l+1) &= \mathbf{f}(\mathbf{x}(k+l),\mathbf{u}(k+l)),\\
\mathbf{y}(k+l) &= \mathbf{g}(\mathbf{x}(k+l),\mathbf{u}(k+l)),\\
\mathbf{h}(\mathbf{x}(k+l),\mathbf{u}(k+l)) &\geq 0,\\
&\text{for } l = 0,\cdots,N-1,
\end{aligned}$$

where $\mathbf{x}$ is the state vector, $\mathbf{y}$ is the output vector, and $\mathbf{u}$ is the control input vector. J is the cost function of optimization. The functions $\mathbf{f}$ and $\mathbf{g}$ represent state equations and output equations, respectively, of the state space model. The function $\mathbf{h}$ represents inequality constraints of the system. N is the prediction horizon and k is the discrete time step.

As illustrated in (2.1), the cost function J is minimized over the prediction horizon N thus taking into account the cost over the predicted time horizon. The dynamics of the system are incorporated in a discrete time state space model given by the state equations $\mathbf{f}$ and the output equations $\mathbf{g}$. These equations constitute equality constraints of the optimization problem. The solution to the optimization problem (2.1) gives the control inputs for the given prediction horizon $\mathbf{u}(k),\cdots,\mathbf{u}(k+N-1)$, such that the total cost over the prediction horizon is minimum.

An optimization problem can be categorized according to the nature of its cost function and its constraints as follows:

- **Linear programming (LP):** If the cost function J, the function of state equations $\mathbf{f}$, and the function of output equations $\mathbf{g}$ are linear functions, then the resulting MPC optimization problem is known as a linear programming (LP) optimization problem.
- **Non-linear programming (NLP):** If one of the above mentioned functions is non-linear, then the MPC optimization problem is a non-linear programming (NLP) optimization problem.
- **Mixed integer non-linear programming (MINLP):** In the case of one or more integer variables, the MPC optimization problem becomes a mixed integer non-linear programming (MINLP) optimization problem.

Depending on the type of the optimization problem, appropriate solvers can be utilized.

The concept of MPC can be used in the model-based control system. The health state models can be converted into the state space model in the MPC. The goals of operational, maintenance, and planning management can be translated to the cost function of the MPC. The prediction horizon of the MPC depends upon the type of management. For operational management, a shorter prediction horizon ranging from milliseconds to hours is required, whereas the prediction horizon for maintenance and planning management ranges from hours to decades [1].

The concept of model-based systems can be implemented as an agent. A description of agents and application of the concept of model-based systems in agents is given in the next section.

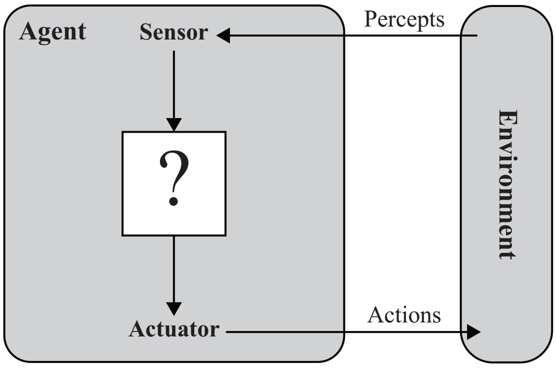

Figure 2.2: Interaction of an agent with its environment through sensors and actuators [18]. The agent generates actions based on percepts from the environment.

2.4 Intelligent agents

An agent, in the context of this thesis, is defined as a system which can perceive its environment through sensors and acts autonomously upon that environment through effectors (see Figure 2.2) [18]. An intelligent agent can sense the environment and take the best possible action in a given situation. According to [19], an intelligent agent has the following properties:

- **autonomy:** agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
- **social ability:** agents interact with other agents (and possibly humans) via some form of agent-communication language;
- **reactivity:** agents perceive their environment (which may be the physical world, a user via a graphical user interface, a collection of other agents, the Internet, or perhaps all of these combined), and respond in a timely fashion to changes that occur in it;
- **pro-activeness:** agents do not simply act in response to their environment they are able to exhibit goal-directed behavior by taking the initiative.

A stronger notion of agents describes these as having the above mentioned properties and human-like attributes [19] so that agents are capable of solving the problems in a similar way as humans do. They have the ability to learn so that they can also evolve to deal with the changing environment.

The agent concept does not have a minimum requirement or a precise guideline that has to be followed to qualify for being an agent. The agent concept is a way of solving problems by dividing the solution of a complex problem into many autonomous and well-structured solutions and coordinating the well-structured solutions to achieve the goal [20]. An agent should have a well-defined task description and should be able to perform its task by communicating with other agents and/or the physical environment.

Various types of agents are used in different systems. According to [18], agents can be classified into four categories, given by:

1. **Simplex reflex agent:** This agent generates action based on the current percept based on a set of rules.

2. **Model-based reflex agent:** This agent maintains an internal state of its environment. The internal state is created from the model of the environment and the percepts obtained from the sensors. A set of rules is established which generates required actions based on the internal state.

3. **Goal-based agents:** Like in model-based reflex agent, a goal-based agent also keeps an internal state of the environment. The goal of the agent is set and the agent generates actions which will lead to this goal.

4. **Utility-based agent:** This agent also maintains an internal state as in the previous two types of agents. In addition, it has a utility function which maps a set of internal states to a performance index. The actions are chosen such that the performance index is optimized.

The simplex reflex agent gives a one-to-one mapping between the current percepts and the current actions, whereas the model-based reflex agent, the goal-based agent, and the utility-based agent use the model of the environment to predict the effect of the action. In the model-based reflex agent, actions are determined by a set of rules. These rules are difficult to adapt in the case of abnormal operating conditions [18]. The goal-based agent has the advantage of being driven by the desired result, though it is not efficient if the agent has multiple conflicting goals. The concept of the utility-based agent can handle multiple goals. The utility-based agent is discussed in the next section.

2.4.1 Utility-based agent

A schematic diagram of the utility-based agent is given in Figure 2.3 [18]. It has a model of the environment and evaluates "what the world is like now" from the percepts. The state of the environment is estimated by the model. Using the model, the evolutions of the state due to different actions are predicted. The set of the sequence of states due to a particular action is given a performance index by defining a utility function. The utility function provides a degree of happiness based on the subsequent sequence of the states. The calculation of the performance index is particularly beneficial if there are multiple goals of the agent. A trade-off between the goals can be achieved by associating a performance index to each goal. The agent then determines the optimal action by choosing one which gives the maximum performance index.

The utility-based agent closely follows the philosophy of model-based control in the sense that the essence of the behavior of the environment is captured within the agent. The agent considers "what the world is like now" and "what my actions do". By using a "utility" function to evaluate the effectiveness of the possible actions, an optimization is performed by the agent. The concept of utility-based agent can be extended to include the model-based control, which is presented in the next section.

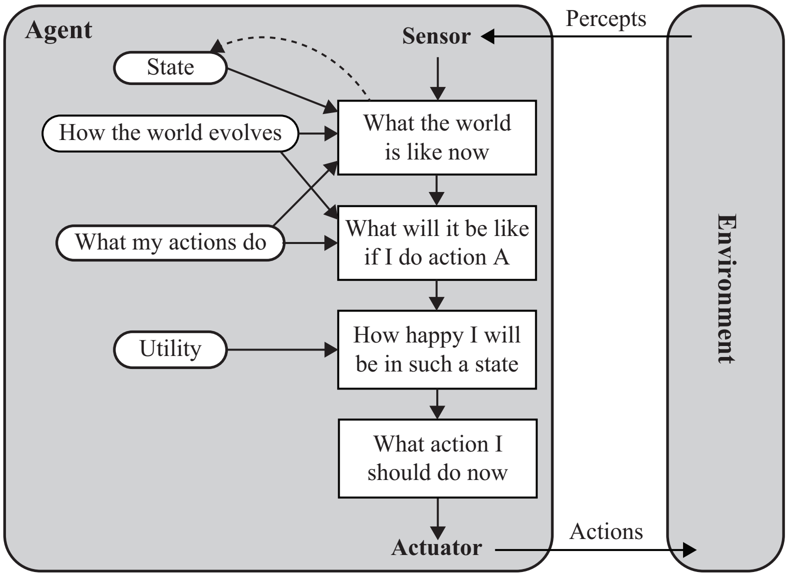

Figure 2.3: Utility-based agent [18] uses a utility function to evaluate the degree of happiness of different plans. The action resulting in the greatest degree of happiness is chosen.

2.4.2 Model-based optimization agent

We propose a concept of the model-based optimization agent which works according to the principle of model-based control presented in Section 2.3. A schematic diagram of this agent is shown in Figure 2.4. In this agent, the model of the system (environment) and the optimizer is embedded as shown in the figure. The model predicts the effects of the possible action within a prediction horizon. Effectively, the model is estimating "what the world is like now" and is predicting "what will it be like if I do action A".

The optimizer determines the degree of happiness by evaluating the cost of a particular action using the cost function of the optimization problem. The optimizer seeks an optimal action, which results in the least cost. In this process, the agent is performing iterations of steps "what will be like if I do action A" and "how happy I will be in such a state". The process of these iterations is also illustrated in Figure 2.4.

One of the advantages of incorporating the model-based optimization concept within an agent is the ability of using various optimization algorithms developed for model-based control [16]. The constraints of the system can also be taken into account in the optimization problem. Furthermore, the social ability of an agent can also be exploited to achieve the distributed control.

2.5 Distributed approach

In principle, a control problem can be solved using a centralized controller. An MPC problem can be formulated which incorporates the whole control problem. However, as the

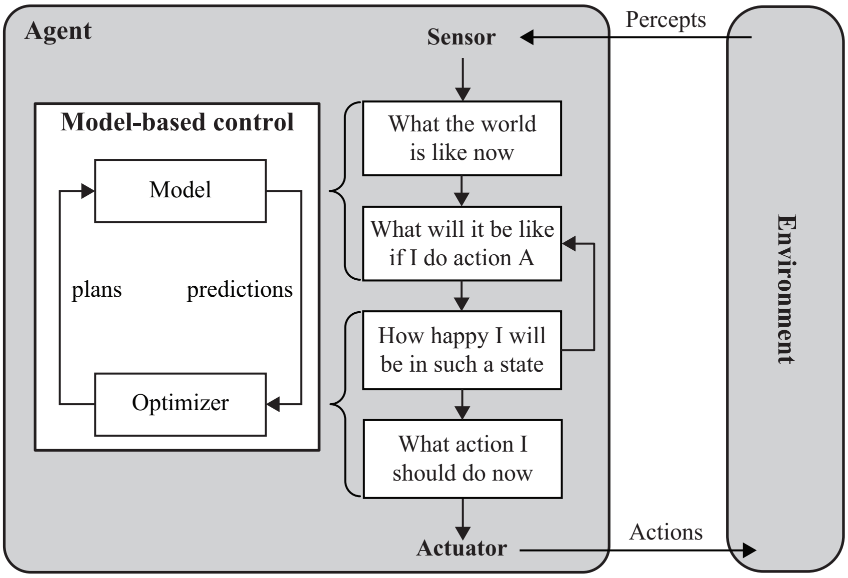

Figure 2.4: Model-based optimization agent incorporates model-based optimization for determining an optimal action. The model estimates "what the world is like now" and predicts "what will it be like if I do action A". The optimizer evaluates "how happy I will be in such a state" and decides "what action I should do now".

system to be controlled and the aspects to be controlled become more complex, the centralized control strategy tends to become more complex and unmanageable. In order to solve the complex problem in a manageable and efficient way, the problem can be divided into simpler sub problems. Solutions to each of these sub problems can be developed independently. These solutions to the sub problems can then be combined and coordinated in order to solve the complex problem [16], [20].

In Section 1.1, a three layered control of the electricity grid based on the perspective of time was proposed. The operational management's time response ranges from milliseconds to hours. The maintenance management takes hours to years. The planning management has a long-term time window of years to decades. The total management problem of the electricity grid can be decomposed based on these time-based categories. For each level of management, a distributed controller can be designed. These controllers should include relevant models of the electricity grid and the equipment according to their goals and their time frames. For each controller, a model-based control strategy can be developed and implemented in a distributed approach. The schematic of the distributed control is given in Figure 2.5.

The three levels of management are inter-related, as the control actions in one level has an effect on other levels. An effective total management of the grid is only possible if the interactions of these three layers are also reflected in the control scheme. Therefore, a hierarchical coordination, as illustrated in Figure 2.5, is proposed. The upper level of management (for instance, the maintenance management) sets goals to the lower level of management (the operational management in this example). The lower level management

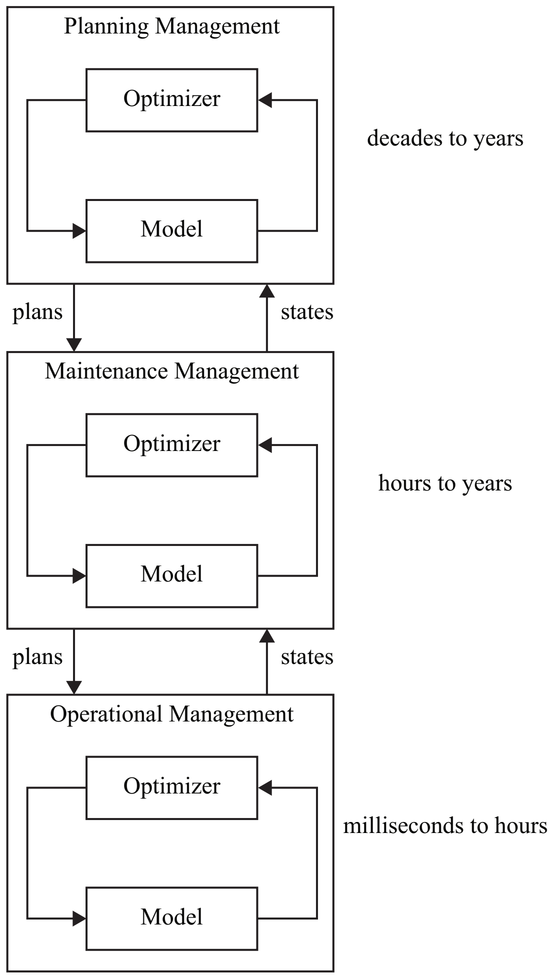

Figure 2.5: Hierarchy of distributed control in the electricity grid. The hierarchy is based on the time span of the management process. The planning management, having the greatest time span, is placed at the top whereas the operational management, having the smallest time span is placed at the bottom of the hierarchy.

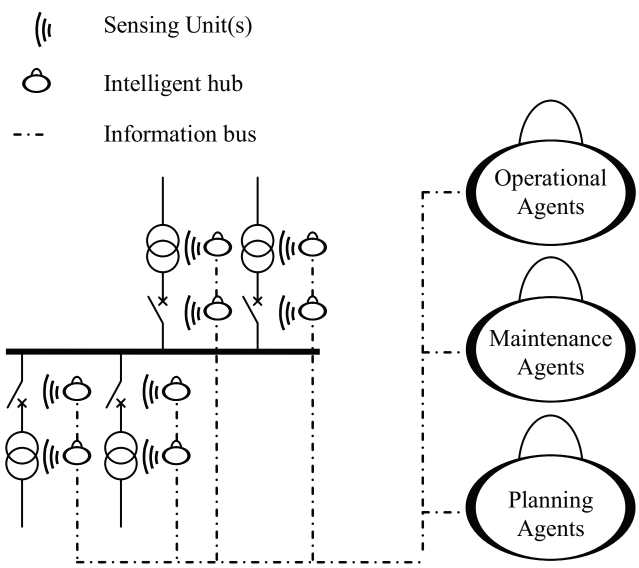

Figure 2.6: An example of agents in the electricity grid. Different sensing units send their measurement to operational, maintenance, and planning agents.

implements the goals received from the upper level management and relays the states back to the upper level management. These states can be taken into account for control of the upper level management.

The distributed approach described above requires coordination between adjacent levels. The social ability of the agents can be exploited for this purpose. The structure of the model-based control system can be achieved by using the model-based optimization agent, described in Section 2.4.2. The model-based optimization agent provides the basis for solving the sub problems. Use of the model of the system to predict effect of possible actions, ensures that the system performance is optimized for the given time horizon in the future.

2.5.1 Agents in electricity grids

Electricity grids consist of different components, such as transformers, cables, overhead lines, switchgears, etc. A schematic diagram of a part of the grid (a substation) is shown in Figure 2.6. In order to incorporate the health state of equipment in its control regime, the following items are required:

- **Intelligent hub:** Instrumentation and intelligence should be added to electrical components so the smart components can assess their condition information and can communicate with other smart components if required. The intelligent hub can perform local actions, such as signal processing of measurements, if required.
- **Operational agent:** Operational agents should be included in order to monitor the health state of the components and give short term recommendations for control based on the health state. The control could include setting the loading limits of the equipment.

- **Maintenance agent:** Based on the present and previous condition of the components and the history of maintenance, maintenance agents should recommend proper maintenance schedules.
- **Planning agent:** Recommendation on long term planning about replacements and/or upgrading should be provided by the planning agents.

Each agent is based on the model-based optimization agent principle. The agent has models of the relevant systems and can predict effects of their actions. An MPC framework is implemented within agents to determine the optimal action. The coordination between the agents is hierarchical in nature, as described above. The agents within the electricity grid can communicate with each other, in order to exchange required information between them. By communicating, the agents introduce interaction between operation, maintenance, and planning management.

2.6 Conclusions

A background of the intelligent systems used in the electricity grid is presented. Knowledge-based systems presently used in the maintenance management of the grid tend to be unmanageable when the operating conditions of the equipment change. In order to incorporate these changes, a model-based control system based on the MPC framework is proposed for the electricity grid. The model-based control system determines the optimal control actions over the prediction horizon.

It is advised that the model-based control system is embedded in an agent framework. The model-based optimization agent is proposed based on existing agent concepts. By using the social ability of the agents, a distributed approach to a global optimization problem is possible. A hierarchy of agents for the operation, maintenance, and planning management of the grid is proposed. Such a hierarchical system divides the complex control problem to simpler control problems. Based on the hierarchical system, the concept of agents in the electricity grid is formulated.

Chapter 3

Intelligent components

Based on the intelligent grid concept presented in Chapter 2, a concept of intelligent components is developed. An intelligent component is based on the model-based optimization agent proposed in Section 2.4.2. The intelligent component is responsible for the optimization problem of a particular aspect of the electrical equipment.

Intelligent components are introduced in Section 3.1. They can make local decisions by considering their local optimization problems. The need of a model-based control for these intelligent components is described in Section 3.2. A model-based optimization framework is developed for making these local decisions, which is laid out in Section 3.3. In order to solve the global problem, an intelligent component should coordinate with other intelligent components in the network. For the coordination, a hierarchal structure of intelligent components is proposed, which is presented in Section 3.4.

The concept of intelligent components is illustrated with an example. In this example, the dynamic loading of transformer based on the hot-spot temperature is developed. The background of thermal loading of the transformer is introduced in Section 3.5. For the model-based optimization, the model of the grid component is required, in this case the thermal model of the transformer (Section 3.6). This thermal model is converted into the model-based optimization framework in Section 3.7. The dynamic loading of the transformer and the simulation results are presented in Section 3.8. This dynamic loading is based on hot-spot temperature predictions. The process of the estimating these temperatures based on the top-oil temperature measurement is given in Section 3.9. The conclusions of this chapter are presented in Section 3.12. The potentials of addition of other predictive health models are described in Section 3.10. In Section 3.11, the evaluation of the accelerated aging of transformers for the given control scheme is illustrated.

Parts of this chapter have been published in [14], [21], [22], and [23].

3.1 Introduction

Components of electricity grids are electrical equipment such as transformers, cables, overhead lines, circuit breakers, etc. These components have to be managed properly in order to improve their reliability and extend their lifetime in a cost effective way. Currently, operation, maintenance, and planning management of these components are based on a set of rules derived from the experience of manufacturers and utilities. The manufacturers make certain assumptions regarding the utilization of the equipment and provide operation, maintenance, and planning guidelines accordingly. During the planning and installation of the equipment, the utilities make a number of assumptions regarding the anticipated operational condition of the equipment (such as loading, aging, and environmental factors). The utilities make operational, maintenance, and planning decisions based on these assumptions and the guidelines provided by the manufacturers.

These decisions are based on a certain scenario of the operational condition of the grid component which is anticipated during the time of its manufacturing, planning, or installation. During the real operational life time of the equipment, its operational condition differs from the anticipated one. This difference is significant in the case of the incorporation of distributed generations from renewable sources. This distributed generation is intermittent in nature and often gives rise to unpredictable bi-directional power flow in the electricity grid [7], thus the loading of the grid component cannot be predicted accurately at the time of planning and installation. As a result, the operational, maintenance, and planning decisions, which are based on the anticipated operational condition, will no longer be optimal decisions.

The effects of these non-optimal decisions accumulate during the operating time of the grid component. At the end, the grid component is either under-utilized or over-utilized. Under-utilization of the grid component means higher costs of management of the grid component as it could have been utilized for more than what has achieved, whereas over-utilization often results in a reduction of its reliability because of the accelerated deterioration of its health-state resulted from the over-utilization.

3.2 Model-based control in an intelligent component

As described in Section 2.3, the utilization of the grid component should be based on the actual operating conditions of the grid component, in order to achieve an optimal utilization of the equipment. The evolution of the health state of the grid component due to changing operation conditions should be tracked. For optimal utilization of the grid component given its function in the network, the operational, maintenance, and planning decisions should be based on its health state. The health state of the equipment can be estimated by monitoring its operational condition and its condition parameters. With the knowledge of its health state, the grid component can take the operational, maintenance, and planning actions when they are required.

A proper and efficient framework is required to incorporate the health information in operational, maintenance, and planning management. The concept of an intelligent component is proposed for this purpose, which has a model of the health state of the grid component as shown in Figure 3.1. Using this model, the intelligent component should be able to keep track of its health state. The concept of model-based control (Section 2.3) can be utilized, in which the evolution of the health state of the grid component is defined in the embedded model. The optimizer can make decisions based on the prediction made by the predictive health model. A framework is presented in the following section.

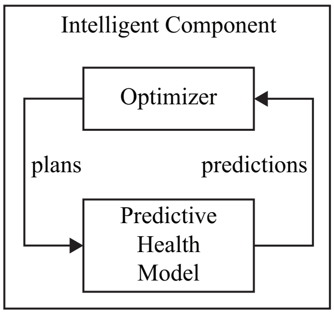

Figure 3.1: Model-based optimization for intelligent components. The optimizer generates plans and the predictive health model returns the effect of the plans on the health state of equipment.

3.3 Framework of model-based optimization

A framework is proposed in order to implement model-based control in intelligent components. This framework of a predictive health model and an optimizer is illustrated in Figure 3.1. Using the predictive health model, the future health state of equipment used in the electricity grid can be predicted for the given possible actions and usage of the equipment. The parts of this framework are outlined below.

3.3.1 Predictive health model

The predictive health model in this framework consists of a dynamic stress model, a failure model, and a model for the estimation of cumulative stresses, as illustrated in Figure 3.2. As equipment ages, various stresses, such as electrical, thermal, mechanical, and environmental stresses weaken the strength of the equipment. These stresses reduce the remaining useful life of the equipment and deteriorate its health state. The health state of the equipment deteriorates due to the cumulative effect of these stresses. Thus, the health state of the equipment is represented by the cumulative stresses. These stresses are affected by the usage pattern (e.g., the loading) and maintenance actions (e.g., the replacement of parts) performed on the equipment. Their dynamics can be described using a dynamic stress model, such as the following discrete-time state space model:

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)), \tag{3.1}$$

where $\mathbf{u}(k) = [\ \mathbf{u}_{\mathrm{a}}(k) \quad \mathbf{u}_{\mathrm{d}}(k)\ ]^{\mathrm{T}}$. At discrete time step k, the future cumulative stresses $\mathbf{x}(k+1)$ are predicted based on the usage of the equipment $\mathbf{u}_{\mathrm{d}}(k)$, the maintenance actions $\mathbf{u}_{\mathrm{a}}(k)$, and the current cumulative stresses $\mathbf{x}(k)$. The set of functions of the discrete-time state space model is given by $\mathbf{f}$.

As the cumulative stresses increase over time, the probability of failure of the equipment also increases. The relationship between the cumulative stresses and the failure rate of the equipment is described in a failure model. This model uses the cumulative stresses to predict the failure rate of the equipment, and directly maps the cumulative stresses to the failure rate as follows:

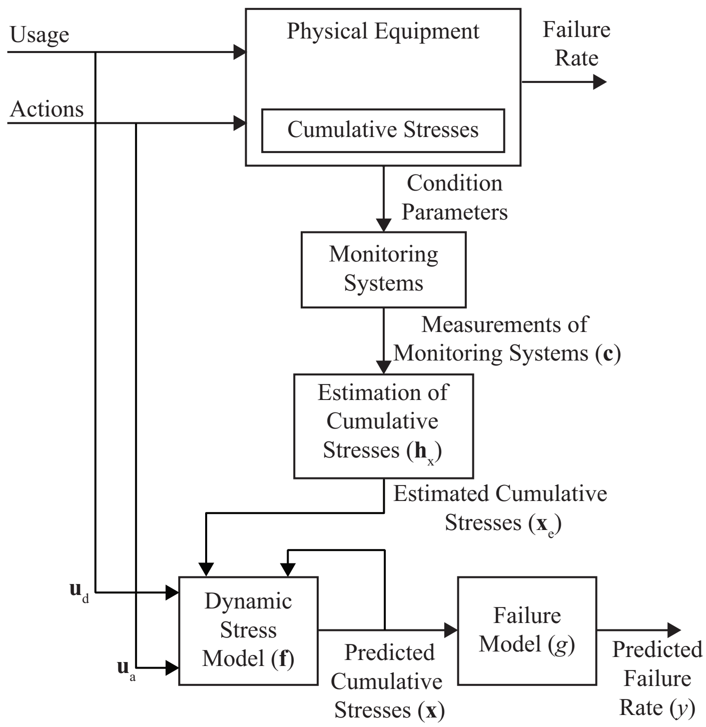

Figure 3.2: Predictive health model which predicts cumulative stresses and failure rate for given usage and actions. Estimation of cumulative stresses obtained from monitoring systems can be used to update the predictive health model.

$$y(k) = g(\mathbf{x}(k), \mathbf{u}(k)), \tag{3.2}$$

where $y(k)$ is the failure rate and g describes the function of the failure model.

The cumulative stresses can be estimated by condition parameters of the equipment, such as partial discharges, temperature measurements, etc. Different online and offline monitoring systems can be used to detect these condition parameters. These monitoring system can be used to estimate the cumulative stress. In the case of online monitoring system, the cumulative stresses can be estimated online, whereas in the case of offline monitoring systems, the results of the monitoring system has to be entered into the system and then the estimated cumulative stresses could be calculated. In practice, only a few condition parameters (such as the electrical and thermal stresses) are measured by monitoring systems. Estimations of the monitored cumulative stresses can be made based on these measurements as follows:

$$\mathbf{x}_\mathrm{e}(k) = \mathbf{h}_\mathrm{x}(\mathbf{c}(k)), \tag{3.3}$$

where $\mathbf{x}_\mathrm{e}(k)$ are the estimated cumulative stresses, $\mathbf{c}(k)$ are the measurements of the monitoring systems, and $\mathbf{h}_\mathrm{x}$ describes the set of functions which estimate the cumulative stresses based on the measurements.

The estimated cumulative stress estimates $\mathbf{x}_\mathrm{e}(k)$ can be used in the dynamic stress model to update the corresponding cumulative stresses. The remaining unmonitored cumulative stresses are predicted by the dynamic stress model.

The framework of the predictive health model can be used to predict the health state and the failure rate of equipment by taking in account its usage and the performed maintenance actions. The measurements of the monitoring systems can be used to update the cumulative stresses of the equipment.

3.3.2 Optimization of maintenance and usage

Typically, maintenance improves the health state of the equipment, which, in turn, reduces its failure rate. Usage of the equipment also affects the cumulative stresses, thus has an influence in the failure rate. An optimal maintenance action and usage balances the economical cost of the maintenance, the cost of the usage, the improvement of the health state, and the reduction of the failure rate of the equipment. The usage indicates the utilization of the equipment.

The total cost of the usage and the maintenance actions is defined to consist of three sub-cost functions. The sub-cost function of the planned usage and the maintenance actions J_a incorporates the economical cost of the maintenance and the cost of usage. The sub-cost function of the failure rate J_f takes into account the cost associated with the failure of the equipment. The sub-cost function of the cumulative stresses J_cs incorporates the cost of the deterioration of the equipment. The summation of these three sub-cost functions gives the total cost of a particular maintenance action in a particular state.

The optimization of the usage and the maintenance actions is considered over a given predicted time frame of N steps in the future, such that future usage and future maintenance actions can be optimized. The total cost over the predicted time frame is considered in the optimization. Hence, the model-based optimization problem is formulated as follows:

$$\min_{\mathbf{u}(k),\ldots,\mathbf{u}(k+N-1)} \left[\sum_{l=0}^{N-1} J_{\mathrm{a}}(\mathbf{u}(k+l)) + \sum_{l=0}^{N-1} J_{\mathrm{f}}(y(k+l)) + \sum_{l=0}^{N-1} J_{\mathrm{cs}}(\mathbf{x}(k+l)) \right], \tag{3.4}$$

subject to

$$\begin{aligned} \mathbf{x}(k+l+1) &= \mathbf{f}(\mathbf{x}(k+l),\mathbf{u}(k+l)), \\ y(k+l) &= g(\mathbf{x}(k+l),\mathbf{u}(k+l)), \\ \mathbf{h}(\mathbf{x}(k+l),\mathbf{u}(k+l)) &\geq 0, \\ &\text{for } l = 0,\ldots,N-1. \end{aligned}$$

The predictive health model is thus used to predict the cumulative stresses and the failure rates for the planned usage pattern and different future maintenance actions. The total cost is evaluated for different future usage and maintenance actions over the predicted time frame. The optimal usage and maintenance actions which are minimizing the total cost over the time horizon are searched for.

3.4 Hierarchical structure of intelligent components

The operational, maintenance, and planning managements are organized in a three-tier hierarchical structure, which is based on the perspectives of time of such management systems. The planning management, which has the longest time span, is at the top of the hierarchy, and the operational management, which has the shortest time span, is at the bottom, as was shown in Figure 2.5.

The upper management agent in the hierarchy sends plans to its lower management agent and the lower management agent provides its predicted states to the upper management agent (see Figure 3.3). For a particular agent of the management system, the plan obtained from its upper level agent is a guideline or a set point for its operation. The intelligent agent functions according to the guidelines and optimizes its performance according to the received plan. It then sends its predicted states back to its upper level agent. The intelligent agent also formulates the plan for its lower level agent. The lower level agent returns its predicted state to the intelligent agent.

A particular management agent could consist of multiple sub-management agents in a sub-hierarchy. An example of such a multi-agent system within the operational management agent will be presented in Chapter 4.

The main advantage of having such a hierarchical structure is that the whole complex problem can be divided into simpler sub-problems. As a result, the underlying health model of the particular sub-problem is also simplified. The optimization problem for the simplified model also becomes more tractable than the global optimization problem for the whole complex system. In order to solve the global problem, these sub-problems have to be coordinated. This coordination is achieved by exchanging of plans and states between the upper and the lower level agents. The upper level agent sets guidelines for its lower level agent through plans. The lower level agent works according to the obtained guidelines and provides the result of the guidelines, in terms of the predicted health state to the upper level agent.

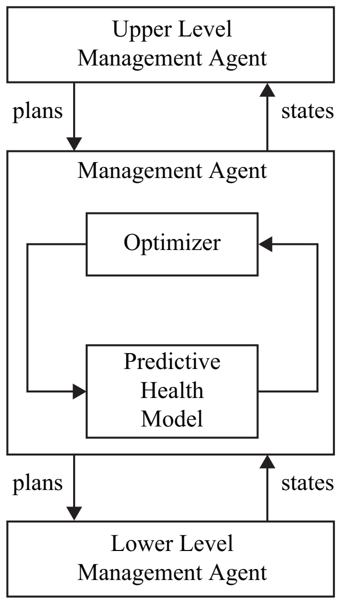

Figure 3.3: Hierarchy of intelligent components. The upper level agent has a longer time span and the lower level agent has a shorter time span. A management agent sends its predicted states to and receives plans from its upper level agent. Similarly, a management agent receives predicted states of its lower level agent and formulates plans for its lower level agent. There can be multiple agents in any level and one agent can interact with multiple agents.

3.5 Thermal loading of a transformer

Traditionally, the loading limit of the transformer is set by its nominal rating. This nominal rating is based on the thermal capability of the transformer under specified conditions. However, in the real operating environment, these conditions can vary so the loadability of the transformer can be changed. A dynamic loading can be formulated for the transformer in which the loading limit changes dynamically based on its conditions. The concept of intelligent components and the framework of model-based optimization are applied in the dynamic loading, based on its thermal performance.

3.5.1 Thermal effects in a transformer

A transformer consists of various sub-components, such as windings, cellulose paper insulation, a core, tap changers, etc. The health of a transformer depends on the health state of its sub-components. One of the important sub-components is the cellulose paper insulation which often dominates remaining lifetime of the transformer. Degradation of the cellulose paper insulation, due to thermal stress, oxidation, and hydrolytic processes reduces its dielectric and mechanical strength. This cellulose degradation determines the operating life of the insulation system [24].

Among the degradation processes of the paper insulation, oxidation and hydrolytic processes depend upon external factors. These external factors include the quality of the moisture absorbers in the breathers, leakage in the transformer tank, humidity of the surroundings, etc. However, the thermal degradation process is related to its operational conditions, such as the loading of the transformers. Thus, the temperatures within a transformer are important factors for its operation. Below, we discuss the different types of temperatures that play a role and their consequences for transformer loading requirements.

3.5.2 Temperatures in a transformer

The main sources of heat generated within a transformer are losses in its magnetic core and in its windings. The core losses depend on the applied voltage of the transformer; the winding losses depend on the loading (current) of the transformer. Other stray losses (constituting losses due to the leakage flux, the winding connection, and the terminal connections) also contribute to the heating of the transformer. In the case of an oil-immersed transformer, the heat dissipated in the core, the windings, and the other parts is transferred to the oil. Subsequently, the heat is transferred from the oil to the cooling medium via the radiators. This gives a gradient in temperature, resulting in different temperatures for the top part of the oil, the bottom part of the oil, and different sections of the windings. In general operation of transformers, the temperature of the windings is highest, followed by the temperature of top part of the oil and the temperature of the bottom part of the oil. Different temperatures in the different locations within the transformer are defined as illustrated in Figure 3.4. In the figure, the horizontal axis gives the magnitude of these temperature whereas the vertical axis indicates the vertical location of these temperature within the transformer.

The winding material in a transformer can withstand temperatures of several hundreds degrees Celsius and the oil does not degrade significantly below 140 °C [25]. However, insulation paper that surrounds the windings in a transformer degrades increasingly rapidly

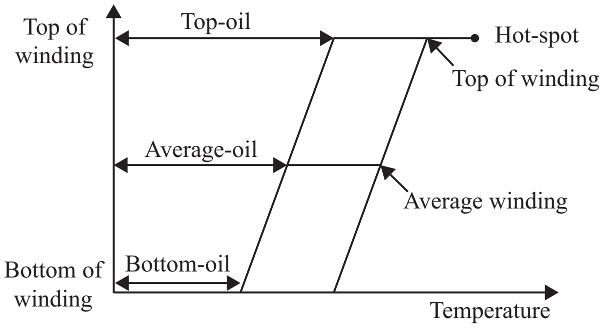

Figure 3.4: Distribution of oil temperatures and winding temperatures of a transformer along the vertical direction inside the transformer tank [25], [26].

as the temperature exceeds 90 °C. This degradation process reduces the dielectric and mechanical strength of the insulation paper, hence reduces its life time [14], [24], [26] [27], [28].

The top-oil and the bottom-oil temperatures are often measured with temperature sensors embedded in the transformer. The hot-spot temperature is defined as the temperature of the hottest part of the windings. This temperature is also the maximum temperature of the paper insulation, which is closely wrapped around the conductors of the windings. Thus, this temperature is used for determining the level of the paper degradation [27].

Transformers are designed considering a hot-spot temperature of 110 °C. The rated loading of a transformer is defined such that its hot-spot temperature reaches 110 °C at this loading. The per unit life of the paper insulation at this reference temperature is considered to be equal to unity. According to [27], per unit life of the paper insulation with respect to the hot-spot temperature is formulated as follows:

$$\text{per unit life} = 9.80 \times 10^{-18} \exp\left(\frac{15000}{\theta_{\text{hs}} + 273}\right), \tag{3.5}$$

where θ_{hs} is the hot-spot temperature of the transformer.

According to the definition, the per unit life would be equal to 1 when θ_{hs} is 110 °C. The aging acceleration factor is defined as a factor by which the life of the insulation paper is increased (or decreased) with reference to the life of the insulation paper with a hot-spot temperature of 110 °C . Thus this aging acceleration factor can calculated from (3.5) as follows:

$$\mathrm{F}_{\mathrm{AA}} = \exp\left(\frac{15000}{383} - \frac{15000}{\theta_{\text{hs}} + 273}\right), \tag{3.6}$$

where F_{AA} is the aging acceleration factor.

The relation between the hot-spot temperature and the aging acceleration factor of the paper insulator is illustrated in Figure 3.5. As seen in the figure, the rate of aging increases with an increased hot-spot temperature.

During normal operation of a transformer, the hot-spot temperature depends on the loading. Thus, the transformer loading determines the aging rate of the insulation paper.

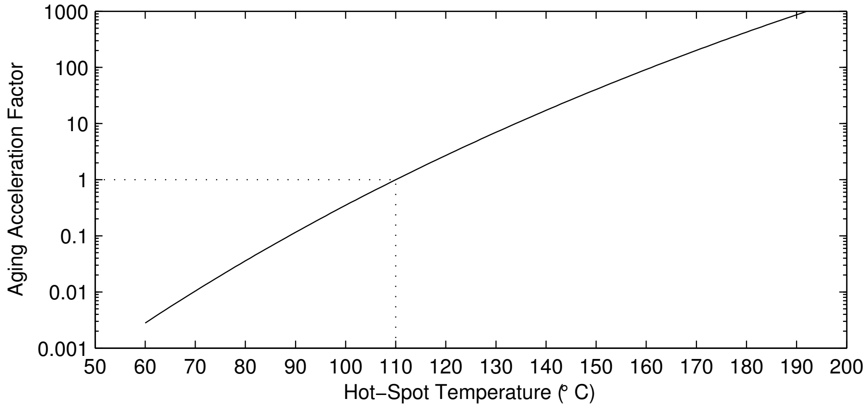

Figure 3.5: Aging acceleration factor of paper insulation based on its hot-spot temperature. Normalized aging factor of unity is considered for a hot-spot temperature of 110 °C *[27].*

Table 3.1: Suggested maximum hot-spot temperature for different types of loading regimes in IEEE C57.91 [27].

Types of loading regimes	**Maximum hot-spot temperature [°C]**
Normal life expectancy loading	120
Planned loading beyond nameplate	130
Long-time emergency loading	140
Short-time emergency loading	180

3.5.3 Loading of a transformer

The maximum allowable loading of a transformer mainly depends on the thermal performance of the transformer. IEEE C57.91 [27] defines four types of loading regimes, for which the suggested maximum hot-spot temperature is given in Table 3.1.

- **Normal life expectancy loading** is defined as the normal loading of the transformer, which does not accelerate the aging process of the transformer. Under normal life expectancy loading the maximum hot-spot temperature allowed is 120 °C.

- **Planned loading beyond nameplate** is suggested for a planned, repetitive load, provided that the transformer is not loaded continuously at the rated load. The duration of this kind of loading should be determined by loss of insulation life calculations for the specific load cycle of the transformer.

- **Long-time emergency loading** is suggested only for rare emergency conditions, such as outage of some part of the network, which results in overloading of the particular transformer. This type of loading is suggested for only two or three times over the normal lifespan of a transformer. The duration of such loading could last up to several months, taking the loss of insulation life and the risk associated with it into consideration.
- **Short-time emergency loading** is only suggested for a short time in very rare emergency conditions such as second contingency (when two equipment fail) or third contingency (when three equipment fail) of the network. This type of loading is only recommended for one or two times over the lifespan of a transformer.

Normal life expectancy loading is considered risk free [27]. This loading regime is considered in this chapter. In the other three cases, the calculation of the loss of life due to the loading and the risk of failure associated with this should be considered.

3.6 Thermal models of a transformer

The dynamics of the top-oil temperature and the hot-spot temperature are described in the top-oil model and the hot-spot model, respectively. In the top-oil model, the top-oil temperature is calculated based on the ambient temperature and on the dynamics of the heat transfer from the oil to the environment through the radiators. Similarly, the hot-spot temperature is calculated based on the top-oil temperature and on the dynamics of the heat transfer between the windings and the oil. The dynamics of the top-oil temperature and the hot-spot temperature can be described by first order differential equations with specific time constants. The time constants of the dynamics of the top-oil and hot-spot temperatures are the top-oil time constant and hot-spot time constant, respectively.

IEEE C57.91 [27] suggests a top-oil time constant based on the mass of different parts and on the cooling type of the transformer. The winding time constant, which describes the dynamics of the heat transfer between the windings and the oil, is estimated based on cooling experiments. Swift et al. [28] propose a thermal model based on heat transfer theory, which includes thermal capacitances and non-linear thermal resistances. Susa et al. [25], [29] extend this approach by considering the oil viscosity changes and the loss variation with the temperature. Their thermal model consists of the top-oil model and the hot-spot model, as presented below.

3.6.1 Top-oil thermal model

The top-oil model presented here is derived from [25], [29]. The top-oil temperature depends on the load factor and the ambient temperature. The load factor is the actual load of the transformer represented in the per unit (pu) system, with the rated loading of the transformer as the base unit (i.e. 1.0 pu). The dynamics of the top-oil temperature θ_{oil} are described by:

$$\frac{1+RK^2}{1+R}\mu_{\text{pu}}\left(\theta_{\text{oil}}\right)^n \Delta\theta_{\text{oil,rated}} = \mu_{\text{pu}}\left(\theta_{\text{oil}}\right)^n \tau_{\text{oil,rated}}\frac{d\theta_{\text{oil}}}{dt} + \frac{\left(\theta_{\text{oil}}-\theta_{\text{amb}}\right)^{n+1}}{\Delta\theta^n_{\text{oil,rated}}}, \tag{3.7}$$

where θ_{amb} is the ambient temperature, K is the load factor, R is the ratio of load losses at the rated current, and no-load losses, $\Delta\theta_{\text{oil,rated}}$ is the rated top-oil temperature rise over the ambient temperature, $\mu_{\text{pu}}(\theta_{\text{oil}})$ is the variable oil viscosity in pu, $\tau_{\text{oil,rated}}$ is the rated top-oil time constant, and n is a constant which depends on the type of cooling.

The rated top-oil time constant $\tau_{\text{oil,rated}}$ (in minutes) can be calculated as:

$$\tau_{\text{oil,rated}} = \frac{0.48 M_{\text{FLUID}} \Delta\theta_{\text{oil,rated}}}{P} 60, \tag{3.8}$$

where M_{FLUID} is the mass of the oil in kg and P represents the total losses at the rated load in watts.

The change in viscosity of oil at the top-oil temperature $\mu_{\text{pu}}(\theta_{\text{oil}})$ is given by [30]:

$$\mu_{\text{pu}}(\theta_{\text{oil}}) = \frac{\exp\left(\dfrac{2797.3}{\theta_{\text{oil}}+273}\right)}{\exp\left(\dfrac{2797.3}{\theta_{\text{oil,rated}}+273}\right)}, \tag{3.9}$$

where $\theta_{\text{oil,rated}}$ is the rated top-oil temperature in °C.

3.6.2 Hot-spot thermal model

The hot-spot model presented here is derived from [25], [29]. The hot-spot temperature θ_{hs} is based on the top-oil temperature and the load factor. Its dynamics are described as follows:

$$K^2 P_{\text{cu,pu}}(\theta_{\text{hs}})\, \mu_{\text{pu}}(\theta_{\text{oil}})^n \Delta\theta_{\text{hs,rated}} = \mu_{\text{pu}}(\theta_{\text{oil}})^n \tau_{\text{wdg,rated}} \frac{d\theta_{\text{hs}}}{dt} + \frac{(\theta_{\text{hs}} - \theta_{\text{oil}})^{n+1}}{\Delta\theta^n_{\text{hs,rated}}}, \tag{3.10}$$

where $\Delta\theta_{\text{hs,rated}}$ is the rated hot-spot temperature rise over the top-oil temperature and $\tau_{\text{wdg,rated}}$ is the rated hot-spot time constant. $P_{\text{cu,pu}}(\theta_{\text{hs}})$ is the variable load losses in pu, which is given by:

$$P_{\text{cu,pu}}(\theta_{\text{hs}}) = P_{\text{cu,dc,pu}} \frac{235+\theta_{\text{hs}}}{235+\theta_{\text{hs,rated}}} + P_{\text{cu,eddy,pu}} \frac{235+\theta_{\text{hs,rated}}}{235+\theta_{\text{hs}}}, \tag{3.11}$$

where $P_{\text{cu,dc,pu}}$ are the DC losses in pu, $P_{\text{cu,eddy,pu}}$ are the eddy current losses in pu, and $\theta_{\text{hs,rated}}$ is the rated hot-spot temperature in °C.

3.7 Thermal models in the framework of model-based optimization

In order to implement the model-based optimization framework, the thermal models should be adapted accordingly. The thermal models (3.7), (3.10) are converted to the dynamic stress model (3.1) of the model-based optimization framework. The top-oil temperature θ_{oil} and the hot-spot temperature θ_{hs} are taken as cumulative stresses $x_{\theta,\text{oil}}$ and $x_{\theta,\text{hs}}$, respectively. The load factor K is taken as the usage u_{I}. The ambient temperature θ_{amb} is taken as the exogenous input $u_{\theta,\text{amb}}$. The differential equations (3.7) and (3.10) are discretized by using the forward Euler approximation. The top-oil model discretized from (3.7) is then given by:

$$
\begin{aligned}
\frac{1+Ru_{\text{I}}(k)^2}{1+R}\mu_{\text{pu}}(k)^n\Delta\theta_{\text{oil,rated}} = \mu_{\text{pu}}(k)^n\tau_{\text{oil,rated}}&\frac{x_{\theta,\text{oil}}(k+1)-x_{\theta,\text{oil}}(k)}{h} \\
&+\frac{(x_{\theta,\text{oil}}(k)-u_{\theta,\text{amb}}(k))^{n+1}}{\Delta\theta^n_{\text{oil,rated}}},
\end{aligned}
\tag{3.12}
$$

where h is the time step and

$$
\mu_{\text{pu}}(k) = \frac{\exp\left(\dfrac{2797.3}{x_{\theta,\text{oil}}(k)+273}\right)}{\exp\left(\dfrac{2797.3}{\theta_{\text{oil,rated}}+273}\right)}. \tag{3.13}
$$

Equation (3.12) can be converted to the dynamic stress model (3.1) as follows:

$$
\begin{aligned}
x_{\theta,\text{oil}}(k+1) &= x_{\theta,\text{oil}}(k)+\frac{h}{\mu_{\text{pu}}(k)^n\tau_{\text{oil,rated}}}\left[\frac{1+Ru_{\text{I}}(k)^2}{1+R}\mu_{\text{pu}}(k)^n\Delta\theta_{\text{oil,rated}}\right. \\
&\qquad \left. -\frac{(x_{\theta,\text{oil}}(k)-u_{\theta,\text{amb}}(k))^{n+1}}{\Delta\theta^n_{\text{oil,rated}}}\right], \\
x_{\theta,\text{oil}}(k+1) &= f_{\text{oil}}(x_{\theta,\text{oil}}(k),u_{\theta,\text{amb}}(k),u_{\text{I}}(k)),
\end{aligned}
\tag{3.14}
$$

where f_{oil} is the state-space function of the top-oil model.

The discretized hot-spot model is then given by:

$$
\begin{aligned}
u_{\text{I}}(k)^2P_{\text{cu,pu}}(k)\mu_{\text{pu}}(k)^n\Delta\theta_{\text{hs,rated}} = \mu_{\text{pu}}(k)^n\tau_{\text{wdg,rated}}&\frac{x_{\theta,\text{hs}}(k+1)-x_{\theta,\text{hs}}(k)}{h} \\
&+\frac{(x_{\theta,\text{hs}}(k)-x_{\theta,\text{oil}}(k))^{n+1}}{\Delta\theta^n_{\text{hs,rated}}},
\end{aligned}
\tag{3.15}
$$

where

$$
P_{\text{cu,pu}}(k) = P_{\text{cu,dc,pu}}\frac{235+x_{\theta,\text{hs}}(k)}{235+\theta_{\text{hs,rated}}}+P_{\text{cu,eddy,pu}}\frac{235+\theta_{\text{hs,rated}}}{235+x_{\theta,\text{hs}}(k)}. \tag{3.16}
$$

Equation (3.15) can be converted to the dynamic stress model (3.1) as follows:

$$
\begin{aligned}
x_{\theta,\text{hs}}(k+1) &= x_{\theta,\text{hs}}(k)+\frac{h}{\mu_{\text{pu}}(k)^n\tau_{\text{wdg,rated}}}\left[u_{\text{I}}(k)^2P_{\text{cu,pu}}(k)\mu_{\text{pu}}(k)^n\Delta\theta_{\text{hs,rated}}\right. \\
&\qquad \left. -\frac{(x_{\theta,\text{hs}}(k)-x_{\theta,\text{oil}}(k))^{n+1}}{\Delta\theta^n_{\text{hs,rated}}}\right], \\
x_{\theta,\text{hs}}(k+1) &= f_{\text{hs}}(x_{\theta,\text{hs}}(k),x_{\theta,\text{oil}}(k),u_{\text{I}}(k)),
\end{aligned}
\tag{3.17}
$$

Table 3.2: Parameters of the 250 MVA transformer used in the thermal model of the case study [26] [29]. Cold start of the transformer is assumed for the case study and thus the initial hot-spot and the initial top-oil temperature are equal.

Parameter	**Value**	**Parameter**	**Value**
$\theta_{\text{oil,rated}}$	75 °C	$\tau_{\text{wdg,rated}}$	6 min.
$P_{\text{cu,dc}}$	411780 W	M_{FLUID}	73887 kg
$P_{\text{cu,eddy}}$	29469 W	$\theta_{\text{oil,i}}$	38.3 °C
P_{s}	43391 W	$\theta_{\text{hs,i}}$	38.3 °C
$\Delta\theta_{\text{hs,rated}}$	20.3 K	R	1000
$\Delta\theta_{\text{oil,rated}}$	38.3 K	n	0.25

where f_{hs} is the state-space function of the hot-spot model.

3.7.1 Simulation of the thermal model

The models (3.12) and (3.15) are simulated for the 250 MVA ONAF (Oil Natural Air Forced-cooled) transformer presented in [26] and [29]. The simulation results are given in Figure 3.6. The parameters used for the simulation are listed in Table 3.2.

The model is simulated for a constant ambient temperature u_{amb} of 25.6 °C. The load profile of the transformer u_{I} for the simulation is 1.0 pu for 190 minutes, 0.6 pu for 175 minutes, 1.5 pu for 135 minutes, 0.3 pu for 210 minutes, 2.1 pu for 25 minutes, and 0.0 pu for 15 minutes, as indicated in Figure 3.6. The model is discretized for a time step h of 1 minute.

The top-oil temperature $x_{\theta,\text{oil}}$ and the hot-spot temperature $x_{\theta,\text{hs}}$ from the simulation are shown in Figure 3.6, which are similar to the results reported in [26] and [29] for the aforementioned load profile. This confirms the top-oil model and the hot-spot model used in this chapter.

3.8 Dynamic loading of transformer based on the thermal model

A dynamic loading agent is proposed for the loading of the transformer, which is shown in Figure 3.7. This agent uses the framework of model-based optimization presented in Section 3.3. According to this framework, the dynamic loading agent consists of a thermal model which is the predicted health model in this case. The optimizer within the agent determines the optimal dynamic loading of the transformer using the thermal model.

A hierarchical structure of agents, as described in Section 3.4, is implemented for this purpose, as shown in Figure 3.7. The upper level agent, loading regime selector agent, provides a maximum hot-spot temperature limit to the dynamic loading agent according to the

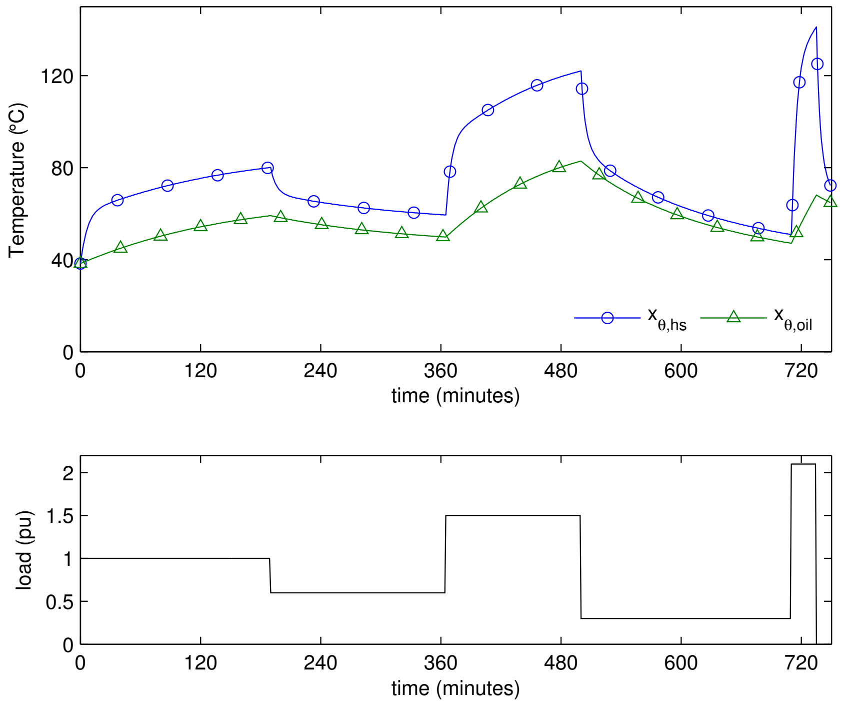

Figure 3.6: Hot-spot and top-oil temperatures (top) for the given load profile (bottom). The load profile is taken from the test case presented in [26] and [29]. The temperature profiles are similar to the results presented in [26] and [29].

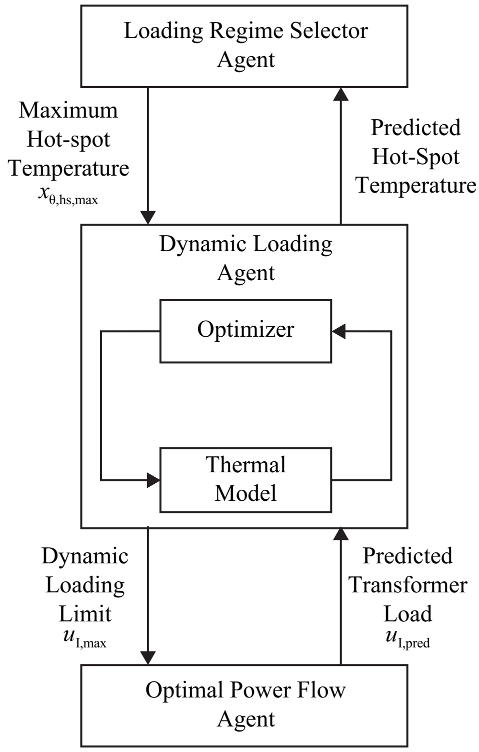

Figure 3.7: Dynamic loading agent and its interaction with the loading regime selector agent and the optimal power flow agent. The dynamic loading agent obtains the maximum hot-spot temperature from the loading regime selector agent and provides the dynamic loading limit to the optimal power flow agent.

selected loading regime (see Table 3.1). This hot-spot temperature limit is derived from one of the four loading regimes given in Table 3.1. The loading regime selector agent chooses one of the loading regimes based on the condition of the transformer and the history of its loading. The dynamics loading agent operates on the recommended regime provided by the loading regime selector agent, by respecting the maximum limit of the hot-spot temperature. The dynamic loading agent sends back the predicted hot-spot temperature to the loading regime agent. This hot-spot temperature is used by the loading regime selector agent to update the condition of the transformer and to determine future loading regimes.

Based on the generation forecast, the load forecast, and the network configuration, the optimal power flow agent predicts the loading of the transformer for the given prediction horizon. Based on this predicted loading and the recommended loading regime, the dynamic loading agent determines the optimal dynamic loading limit of the transformer. This loading limit is transferred to the optimal load flow agent. The optimal load flow agent implements this loading limit by controlling network parameters, such as transformer tap settings, active and reactive power generations, and load controls.

With coordination between these three control agents, a dynamic rating of the transformer is achieved. This dynamic rating is applied by the optimal power flow agent. The selection of the loading regime is accomplished by the loading regime selector agent. The dynamic loading agent described in this section (Section 3.8), uses the thermal model described in Section 3.6.

The other two agents, namely the loading regime selector agent and the optimal power flow agent, will be described in Chapter 4.

Two cases of dynamic loading of transformers are considered in the remainder of this chapter. In the first case the predicted loading of the transformer is known. In the second case the absence of the predicted loading is considered.

3.8.1 Dynamic loading based on predicted loading (load forecast)

The predicted loading of the transformer can be obtained from the optimal power flow agent based on anticipated generations and loads. Based on this predicted loading, the dynamic loading agent sends a time-varying maximum loading limit back to the optimal power flow agent. The optimal power flow agent respects this limit and controls loading of the transformer in such a way that it remains below the given limit.

For the transformer, there are two different kinds of scenarios which may occur in determining the loading limit, these are:

1. **Case 1:** The hot-spot temperature for the given predicted loading is **below** the maximum limit. Thus there is no need of reducing the power flow of the transformer.

2. **Case 2:** The hot-spot temperature for the given predicted loading is **above** the maximum limit. In this case, the loading of the transformer has to be reduced by rerouting the power through other parts of the network.

In Case 1, there is no issue regarding violation of the maximum hot-spot temperature limit. However, there is a possibility of increase (or decrease) in the loading of the transformer due to unforeseen events for example: another transformer in the network could be overloaded and the resulting excess power could be rerouted through the transformer in question. In such a case, the dynamic loading agent should know the maximum loadability of the first mentioned transformer. This can be achieved by giving a maximum loading limit profile for which the maximum hot-spot limit is not violated within the predicted time horizon. This maximum loading limit profile is chosen such that it is proportional to the predicted loading. The motive behind this is to build a proportional cushion around the anticipated loading. If the actual loading is different from the predicted one, it will most likely follow the pattern of the predicted loading. This way the maximum utilization of the transformer can be achieved, even if the actual loading is not the same as the predicted one.

In Case 2, the hot-spot temperature will exceed the maximum limit if the predicted loading is allowed through the transformer. In this case, the only option is to reduce the loading of this particular transformer by rerouting the power through other parts of the network. The power flow rerouting is taken care of by the optimal power flow agent. The dynamic loading agent gives a ‘safe’ loading limit, so that the hot-spot temperature does not exceed the maximum limit. At the same time, there is a need for the maximum utilization of the loading capability of the transformer, so that the net burden of rerouting of the power through other parts of the network is minimized. Thus, for this case a maximum loading limit is provided, which follows the predicted loading as much as possible. In other words, the difference between the maximum loading and the predicted loading is kept at a minimum level.

The desired operation of the agent can be translated into the cost function of the optimization. These two different cases clearly indicate that the cost function of the optimization problem should have 'a kind of' double term to deal with these cases. The optimization problem is summarized as follows:

$$\min_{\alpha, u_{\mathrm{I,max}}(k), \ldots, u_{\mathrm{I,max}}(k+N-1)} \sum_{l=0}^{N-1} \left[c_1 \left(u_{\mathrm{I,max}}(k+l) - \alpha u_{\mathrm{I,pred}}(k+l) \right)^2 \right] - c_2 \alpha, \tag{3.18}$$

subject to

$$\begin{aligned} x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), u_{\mathrm{I,max}}(k+l)), \\ x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), u_{\mathrm{I,max}}(k+l)), \\ x_{\theta,\mathrm{hs}}(k+l+1) &\leq x_{\theta,\mathrm{hs,max}}, \\ \alpha &\geq 1, \\ &\text{for } l = 0, \ldots, N-1, \end{aligned}$$

where $u_{\mathrm{I,pred}}$ is the predicted loading and $u_{\mathrm{I,max}}$ is the maximum loading. c_1 and c_2 are coefficients of the two terms of the cost function. $x_{\theta,\mathrm{hs,max}}$ is the maximum hot-spot temperature. The functions f_{oil} and f_{hs} are the top-oil temperature model (3.12) and the hot-spot temperature model (3.15), respectively. α is a slack variable.

The slack variable α is used to deal with the dual scenarios mentioned in Case 1 and Case 2. The optimization tries to minimize the quadratic term $\left(u_{\mathrm{I,max}}(k+l) - \alpha u_{\mathrm{I,pred}}(k+l)\right)^2$ and to maximize the slack variable α. In Case 1, the maximum loading limit can be more than the predicted loading. Thus, the optimization would maximize the slack variable α while keeping the quadratic term to the minimum, i.e. 0. Effectively, this means that the maximum load will be larger than the predicted load by a factor of the slack variable α which is greater than 1, i.e.:

$$\begin{aligned} u_{\mathrm{I,max}} &= \alpha u_{\mathrm{I,pred}}, \\ \alpha &> 1. \end{aligned} \tag{3.19}$$

As a result, a maximum loading limit $u_{\mathrm{I,max}}$, which is proportional to the predicted loading profile $u_{\mathrm{I,pred}}$, is obtained.

In Case 2, maximization of the slack variable α is not possible as the maximum loading should be less than the predicted load. Thus the slack variable α is set to its minimum value which is 1. Then the optimization attempts to minimize the difference between the maximum loading and the predicted loading, while keeping the hot-spot temperature below its maximum limit.

The optimization problem (3.18) consists of non-linear constraints. The optimization is therefore solved by a non-linear solver, e.g. SNOPT [31]. This solver is used through the Tomlab v6.1 [32] interface in Matlab v7.5. Analytically computed gradients of the constraints and the cost function are supplied to the solver in order to reduce the execution time of the optimization. These gradients are described in Appendix A.

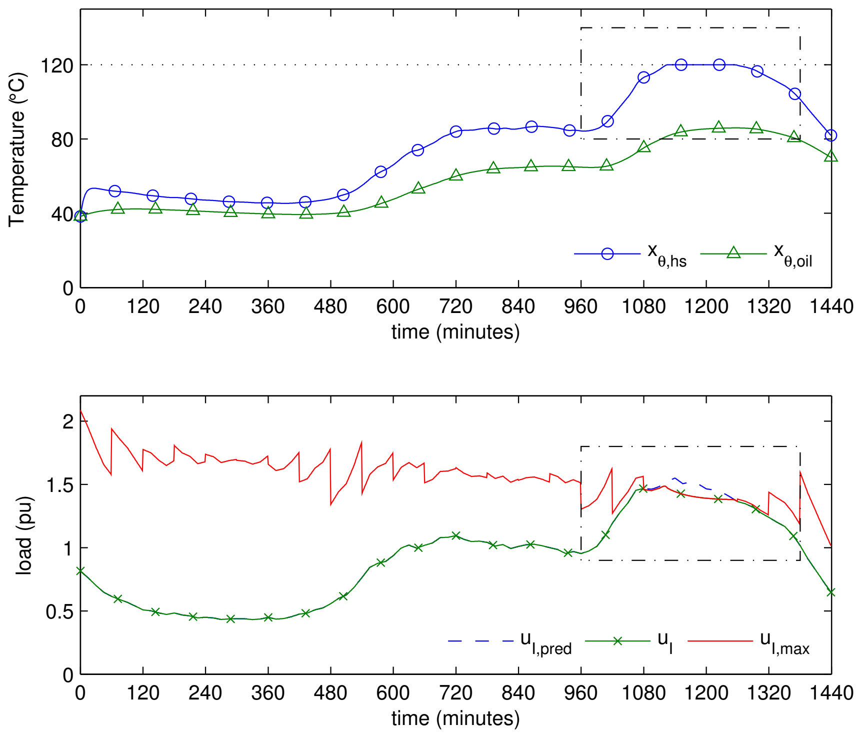

Figure 3.8: Simulation of the dynamic loading of the transformer for 1 day, the prediction horizon is 60 minutes. The area enclosed by the dotted lines is detailed in Figure 3.9. The predicted load (dashed line) equals the actual load for the majority of the day

Simulation

The optimization presented above is solved for the transformer with the parameters given in Table 3.2. A daily load profile of the transformer is assumed, based on the energy demand data for an average Dutch household as given in [16]. This daily load profile is taken as the predicted load $u_{\mathrm{l,pred}}$, which is plotted in Figure 3.8. The loading regime of normal life expectancy loading (Table 3.1) is considered for the maximum hot-spot temperature, i.e. $x_{\theta,\mathrm{hs,max}} = 120\,^{\circ}\mathrm{C}$.

The simulation results for a period of 1440 minutes (1 day) are shown in Figure 3.8. A prediction horizon N of 60 (minutes) is considered for the simulation. The communication between the dynamic loading agent and the optimal load flow agent is done with an interval equal to the prediction horizon (i.e. every 60 minutes).

A zoomed in view of Figure 3.8 is shown in Figure 3.9: for the time interval between 1080 and 1259 minutes, the maximum loading $u_{\mathrm{l,max}}$ is less than the predicted loading $u_{\mathrm{l,pred}}$. In this period the rerouting of the load of the transformer is required in order to

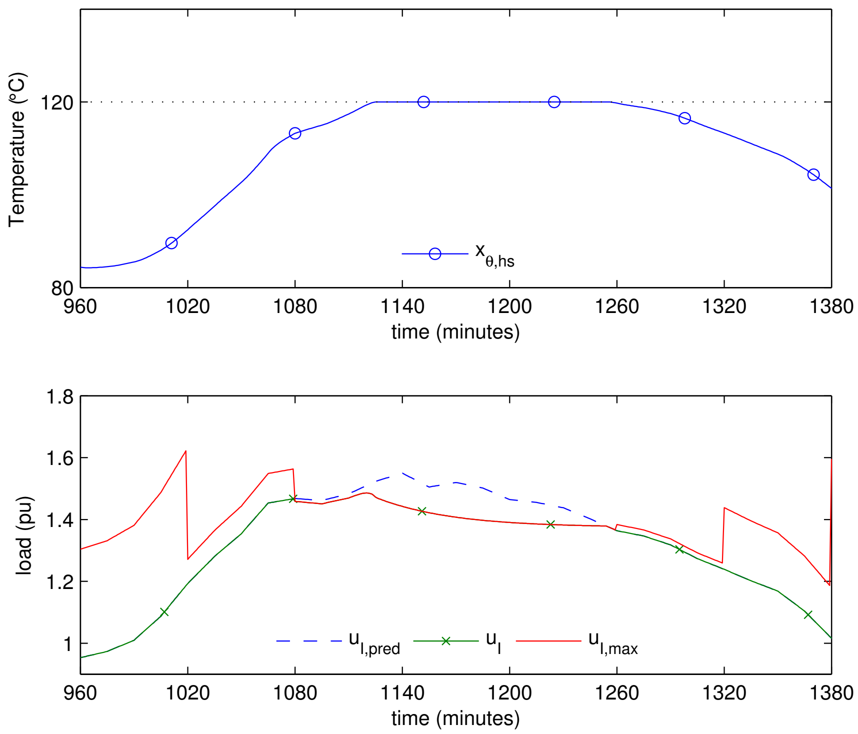

Figure 3.9: Simulation of the dynamic loading of the transformer for the peak load period. A dynamic loading limit $u_{\mathrm{I,max}}$ is provided, the period of the prediction horizon is 60 minutes.

maintain the hot-spot temperature $x_{\theta,\mathrm{hs}}$ below the maximum limit of 120 °C, which was provided by the loading regime selector agent.

In Figure 3.9, the effect of two different terms in the optimization problem (3.18) can also be observed. Between the time interval of 1080 minutes and 1259 minutes, α cannot be increased beyond its minimum value of 1, due to the maximum hot-spot temperature constraint. Thus, the maximum loading is less than the predicted loading. The difference between them is minimized as far as possible. In the remainder of the time interval, the maximum hot-spot constraint is not violated by the predicted loading, thus the slack variable α takes a value greater than 1. Thus the maximum loading is larger than the predicted loading by a factor of α.

Another simulation with a prediction horizon of 15 minutes is presented in Figure 3.10. In this case the maximum loading profile is updated every 15 minutes. Between the period of 1108 minutes and 1253 minutes the actual loading u_{I} of the transformer is less than the predicted (required) loading $u_{\mathrm{I,pred}}$. This is necessary for maintaining the hot-spot temperature $x_{\theta,\mathrm{hs}}$ below its maximum limit of 120 °C.

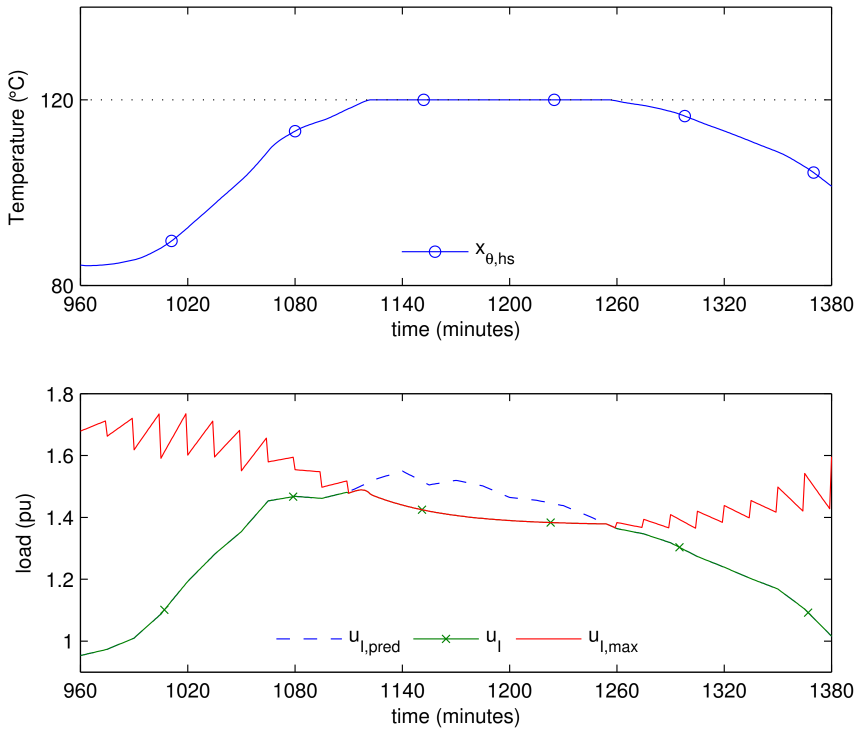

Figure 3.10: Simulation of the dynamic loading of the transformer for the peak load period. A dynamic loading limit $u_{\mathrm{l,max}}$ is provided, the period of the prediction horizon is 15 minutes.

3.8.2 Dynamic loading in absence of predicted loading (load forecast)

In case there would be a of lack of predictions for the loading of the transformer, the dynamic loading agent should make a number of assumptions in order to safely control the loading. Predicting the loading of a transformer could be difficult in the case of a network with renewable energy sources, whose generations are stochastic in nature. The control equipment used in a distribution system has a limited computational capability due to the cost of such equipment. As a result the load forecasting system is often not present, hence the loading of a transformer cannot be predicted accurately.

In such a system the working principle of the dynamic loading agent should be simple enough, so that the control equipment can take the dynamic loading into consideration, along with its other functionalities, such as the metering, control, and protection of the network, and the information exchange support [33]. An example of such a system used in a distribution system is SASensor [34] developed by Locamation Control Systems B.V.

Also the dynamic loading agent proposes a constant loading limit for a certain time period. This limit is based on the current hot-spot temperature and the current top-oil temperature, and is the maximum loading that the transformer could supply for the time period considered, without exceeding the maximum hot-spot temperature limit. The optimization problem for this kind of dynamic loading agent can be formulated as follows:

$$\min_{u_{\mathrm{I,max}}(k),\dots,u_{\mathrm{I,max}}(k+N-1)} \sum_{l=0}^{N-1} -(u_{\mathrm{I,max}}(k+l))^2, \tag{3.20}$$

subject to

$$\begin{aligned}
x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
x_{\theta,\mathrm{hs}}(k+l+1) &\le x_{\theta,\mathrm{hs,max}},\\
u_{\mathrm{I,max}}(k+l+1) &= u_{\mathrm{I,max}}(k+l),\\
&\text{for } l = 0,\dots,N-1.
\end{aligned}$$

This optimization problem simply tries to maximize the constant loading limit without exceeding the maximum hot-spot temperature. This maximum constant loading limit will result in a hot-spot temperature at the end of the prediction horizon $x_{\theta,\mathrm{hs}}(k+N-1)$ equal to the maximum hot-spot temperature $x_{\theta,\mathrm{hs,max}}$. The optimization can be further simplified by solving of a set of equations given as:

$$\begin{aligned}
x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
u_{\mathrm{I,max}}(k+l+1) &= u_{\mathrm{I,max}}(k+l),\\
x_{\theta,\mathrm{hs}}(k+N-1) &= x_{\theta,\mathrm{hs,max}},\\
&\text{for } l = 0,\dots,N-1.
\end{aligned} \tag{3.21}$$

The solution to the set of equations (3.21) gives the maximum loading limit. The algorithm of solving the equations is given in Appendix B. This algorithm requires less coding and less computation power, compared to the algorithm for solving the optimization problem. In other words, by simplifying the optimization problem, the computational requirement of the agent is reduced. Thus, the agent can be incorporated in the existing control system without taking up a major portion of the computation power of the system. The cost of such integration will also be lower than for designing and implementing a dedicated control system just for the purpose of dynamic loading. These factors become crucial in distribution systems where the number of transformers is much higher, and the power delivered by an individual transformer is much less in comparison to transmission systems.

Simulation

The optimization (3.20) is solved for the transformer given in Section 3.8.1 with the operating condition given in the same section. The simulation results for a prediction horizon N of 60 (minutes) are presented in Figure 3.11. As shown in the figure, the maximum loading limit $u_{\mathrm{I,max}}$ provided by this optimization is a constant level for the prediction horizon of 60 (minutes). The optimization does not require the predicted loading $u_{\mathrm{I,pred}}$. However, it is plotted in the figure to provide an impression of the required rerouting of the transformer load. In the period between 1078 and 1253 minutes, the actual loading u_{I} of the transformer is less than the predicted (required) loading $u_{\mathrm{I,pred}}$. As seen in the figure, the hot-spot temperature $x_{\theta,\mathrm{hs}}$ is maintained below the maximum limit of 120 °C by the agent.

Another simulation result with the prediction horizon N of 15 (minutes) is given in Figure 3.12. In this simulation, the maximum loading limit $u_{\mathrm{I,max}}$ for the period of 15 minutes is given at a time. Load control occurs in the period between 1108 and 1253 minutes, during which the actual loading u_{I} of the transformer is less than the predicted (required) loading $u_{\mathrm{I,pred}}$. The hot-spot temperature $x_{\theta,\mathrm{hs}}$ stays below the maximum limit of 120 °C in this simulation.

In the next simulation, a prediction horizon N of 1 (minute) is considered. This means at each time step the optimization calculates the maximum loading the transformer can withstand without exceeding the maximum hot-spot temperature limit of 120 °C. The results of the simulation are given in Figure 3.13. In the period between 1118 and 1254 minutes, the actual loading u_{I} of the transformer is less than the predicted (required) loading $u_{\mathrm{I,pred}}$, in order to maintain that the hot-spot temperature $x_{\theta,\mathrm{hs}}$ stays below the maximum limit of 120 °C, as shown in the figure.

3.8.3 Comparison of simulation results

The dynamic loading of a transformer is considered for two cases. In Section 3.8.1, the predicted loading of the transformer is taking into account while determining the maximum loading limit of the transformer. Two simulations are presented in the section with prediction horizons of 60 minutes and 15 minutes.

In Section 3.8.2 the maximum loading limit is generated based on the current condition of the transformer, without the knowledge of the predicted loading. There three simulations are provided, with prediction horizons of 60 minutes, 15 minutes, and 1 minute. In all cases, the optimization provides the maximum loading of the transformer, with which the hot-spot temperature does not exceed its maximum limit.

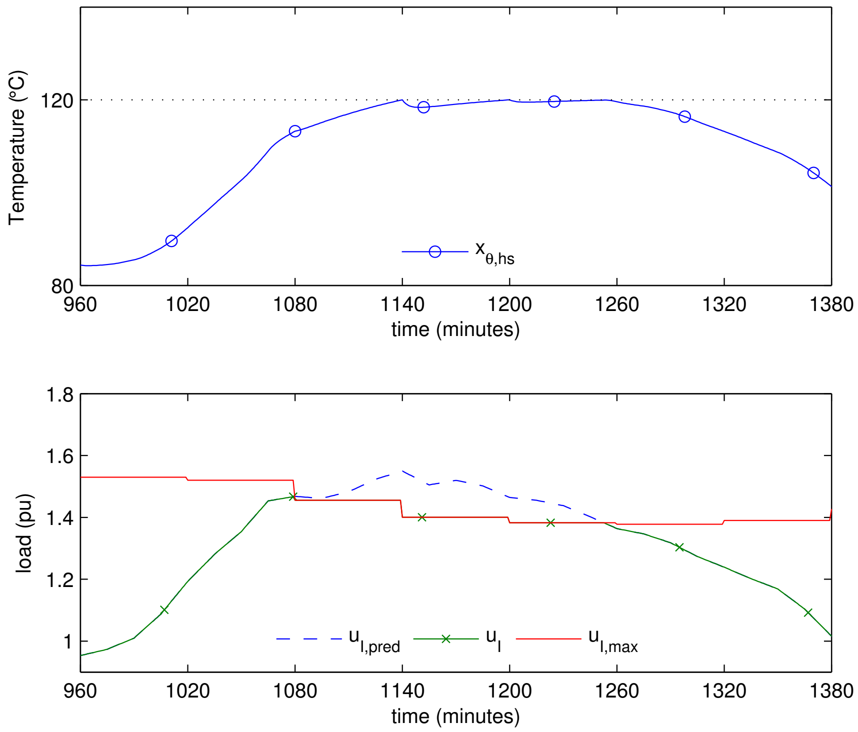

Figure 3.11: Simulation of the dynamic loading of the transformer without information of the load prediction. A constant maximum loading limit $u_{\mathrm{l,max}}$ *is provided after each period of the prediction horizon of 60 minutes.*

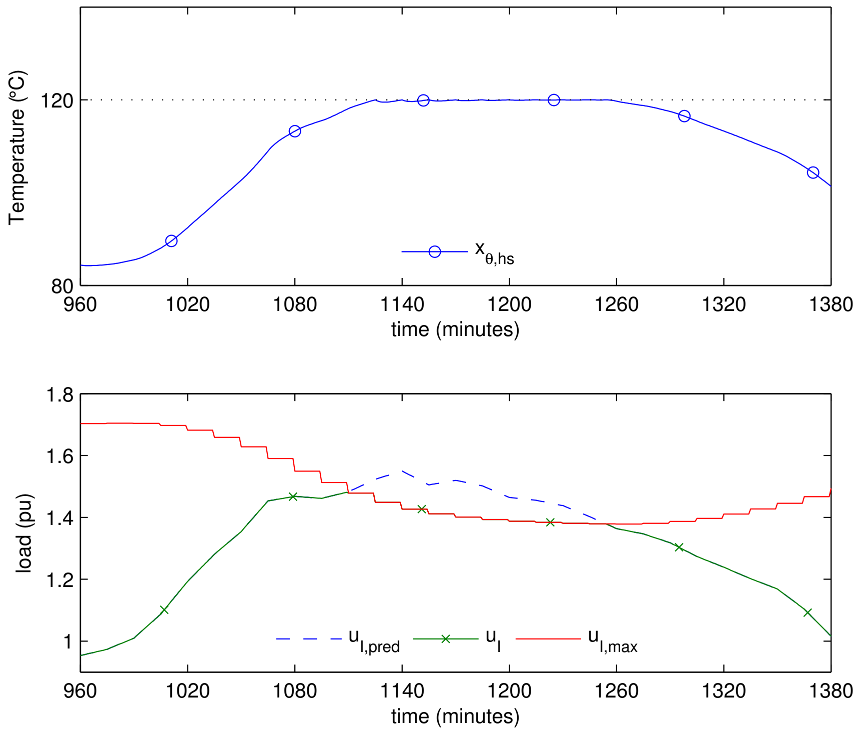

Figure 3.12: Simulation of the dynamic loading of the transformer without information about the load prediction. A constant maximum loading limit $u_{\mathrm{l,max}}$ is provided after each period of the prediction horizon of 15 minutes.

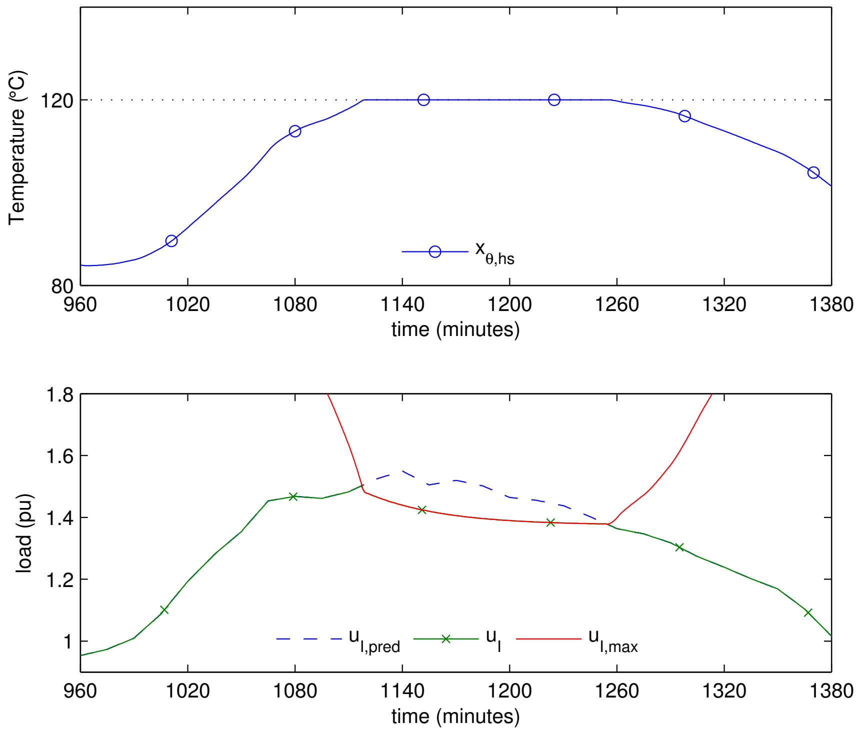

Figure 3.13: Simulation of the dynamic loading of the transformer without information about the load prediction. The maximum loading limit $u_{\mathrm{l,max}}$ is updated at an interval of 1 minute.

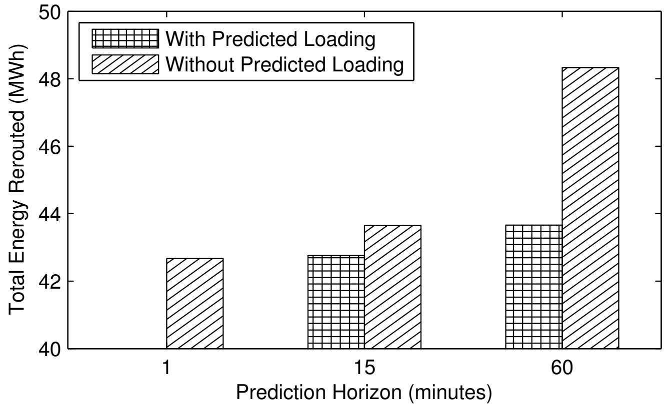

Figure 3.14: Total energy required to be rerouted during the simulation of 1 day. For the same prediction horizon, the rerouted energy is lesser if the predicted loading is available.

The amount of energy rerouted for the simulations presented in both sections is summarized in Figure 3.14. For the simulations without knowledge about the predicted loading (Section 3.8.1), the least energy rerouting is realized for the smallest prediction horizon of 1 minute. This is because the optimization calculates the new loading limit after each time step. This means the communication between the dynamic loading agent and the optimal power flow agent has to be done in a time interval of 1 minute. As the prediction time is increased from 1 minute to 15 minutes and 60 minutes, the rerouted energy increases with each step.

When the predicted loading is taken into account (Section 3.8.1), the energy rerouted is lower than without predicted loading for the same prediction horizon. In addition, the required rerouted energy does not increase as much as in Section 3.8.1 when the prediction horizon increases.

3.9 Estimation of hot-spot temperature from top-oil temperature measurements

Some of the parameters of the health state model can be measured and monitored. Such measurements give more accurate results than the estimations based on a model. They can be incorporated in the predicted health model, so that a hybrid system of models and measurements can be constructed.

For the thermal model of transformers the top-oil temperature is often measurable, as most of the transformers have a top-oil temperature sensor installed during their manufacturing. Thus the measured top-oil temperature can be used instead of using the top-oil temperature model to estimate it.

The measured top-oil temperature can be used in the model-based optimization framework in order to improve the accuracy of the model. The measurement is used to update the current top-oil temperature $x_{\theta,\text{oil}}(k)$. The prediction of the hot-spot temperature and the top-oil temperature for the prediction horizon can be done with the predictive health model. In this case the optimization problem (3.18) of Section 3.8.1 can be modified as follows:

$$\min_{\alpha,u_{\text{I,max}}(k),\ldots,u_{\text{I,max}}(k+N-1)} \sum_{l=0}^{N-1} \left[c_1 \left(u_{\text{I,max}}(k+l) - \alpha u_{\text{I,pred}}(k+l)\right)^2\right] - c_2\alpha, \tag{3.22}$$

subject to

$$\begin{aligned}
x_{\theta,\text{oil}}(k+l+1) &= f_{\text{oil}}(x_{\theta,\text{oil}}(k+l), u_{\theta,\text{amb}}(k+l), u_{\text{I,max}}(k+l)),\\
x_{\theta,\text{hs}}(k+l+1) &= f_{\text{hs}}(x_{\theta,\text{hs}}(k+l), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)),\\
x_{\theta,\text{oil}}(k) &= x_{\theta,\text{oil,meas}}(k),\\
x_{\theta,\text{hs}}(k+l+1) &\leq x_{\theta,\text{hs,max}},\\
\alpha &\geq 1,\\
&\text{for } l = 0,\ldots,N-1,
\end{aligned}$$

where $x_{\theta,\text{oil,meas}}(k)$ is the measured top-oil temperature at time step k.

In case of dynamic loading in the absence of the predicted load described in Section 3.8.2, the set of equations (3.21) can be reiterated as follows:

$$\begin{aligned}
x_{\theta,\text{oil}}(k+l+1) &= f_{\text{oil}}(x_{\theta,\text{oil}}(k+l), u_{\theta,\text{amb}}(k+l), u_{\text{I,max}}(k+l)),\\
x_{\theta,\text{hs}}(k+l+1) &= f_{\text{hs}}(x_{\theta,\text{hs}}(k+l), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)),\\
x_{\theta,\text{oil}}(k) &= x_{\theta,\text{oil,meas}}(k),\\
u_{\text{I,max}}(k+l+1) &= u_{\text{I,max}}(k+l),\\
x_{\theta,\text{hs}}(k+N-1) &= x_{\theta,\text{hs,max}},\\
&\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{3.23}$$

3.10 Models for other grid components

The concept of intelligent component can be easily extended to other grid components such as cables, overhead lines and circuit breakers. The predictive health models for these components could be developed and used in the intelligent component framework. Similar to a transformer, loading is the most important factor for determining the health state of cables and overhead lines. The health state of circuit breakers is influenced by number of operations of the breaker among other parameters.

The additional details could also be incorporated into the existing model. Additional parameters which influence the health state of the equipment, such as effect of repetitive transients [4], harmonics, etc., could be incorporated in the model. The new predicted health model could then be used for optimization. The presented framework could be used with the new predictive health model.

3.11 Accelerated aging of transformer under different loading regimes

Four types of transformer loading regimes are described in Table 3.1. The control strategies developed in this chapter can be implemented for any type of loading regime by selecting the corresponding maximum hot-spot temperature limit. Increasing the maximum hot-spot temperature limit accelerates the aging of the transformer. The accelerated aging factor of the transformer for a particular hot-spot temperature can be estimated from (3.6).

In order to evaluate the accelerated aging of the transformer under different loading regimes, the control of loading is simulated for following three loading regimes:

- Normal life expectancy loading: $x_{\theta,\mathrm{hs,max}}$ is 120 °C,
- Planned loading beyond nameplate: $x_{\theta,\mathrm{hs,max}}$ is 130 °C,
- Long-time emergency loading: $x_{\theta,\mathrm{hs,max}}$ is 140 °C.

A case of no loading control is also simulated so that the effect of the control can be observed.

Dynamic loading based on predicted loading (forecast) described in Section 3.8.1 is used for these simulations. A prediction horizon of $N = 15$ is considered. The load profile described in Section 3.8.1 is used. This load profile is increased by a factor. The increased load profile is simulated for three loading regimes mentioned above and the case of no loading control. A range of load profile increment factors is considered in order to evaluate accelerated aging factors for different loading conditions.

Simulations are performed for the duration of 1 day. For each simulation, the accelerated aging factor is calculated based on the hot-spot temperature (according to (3.6)). An average accelerated aging factor is compiled for each simulation. The maximum hot-spot temperature encountered during each simulation is also recorded. The resulting average acceleration factors of these simulations are illustrated in Figure 3.15. Maximum hot-spot temperatures encountered for these simulations are also given in Figure 3.15.

As observed in the figure, the average accelerated aging factor is below 1 for the normal life expectancy loading. For the planned loading beyond nameplate and the long-time emergency loading, the average accelerated aging factor is greater than 1 which indicates that the transformer is aged at an accelerated rate.

The maximum hot-spot temperature is maintained below the corresponding limits of different loading regimes (120 °C, 130 °C, or 140 °C) for all three controlled cases. The maximum hot-spot temperature curves for the three cases of controlled loading deviates from the uncontrolled case. For the planned loading beyond nameplate, the maximum hot-spot temperature levels off at 130 °C after a peak load of 1.58. This deviation indicates that the loading control is activated at this point. Similarly, for the long-time emergency loading, the loading control initiates at a peak load of 1.685.

The results shown in this chapter is dependent on the shape of the profile. A flatter profile with a higher load factor would result in a greater accelerated aging factor.

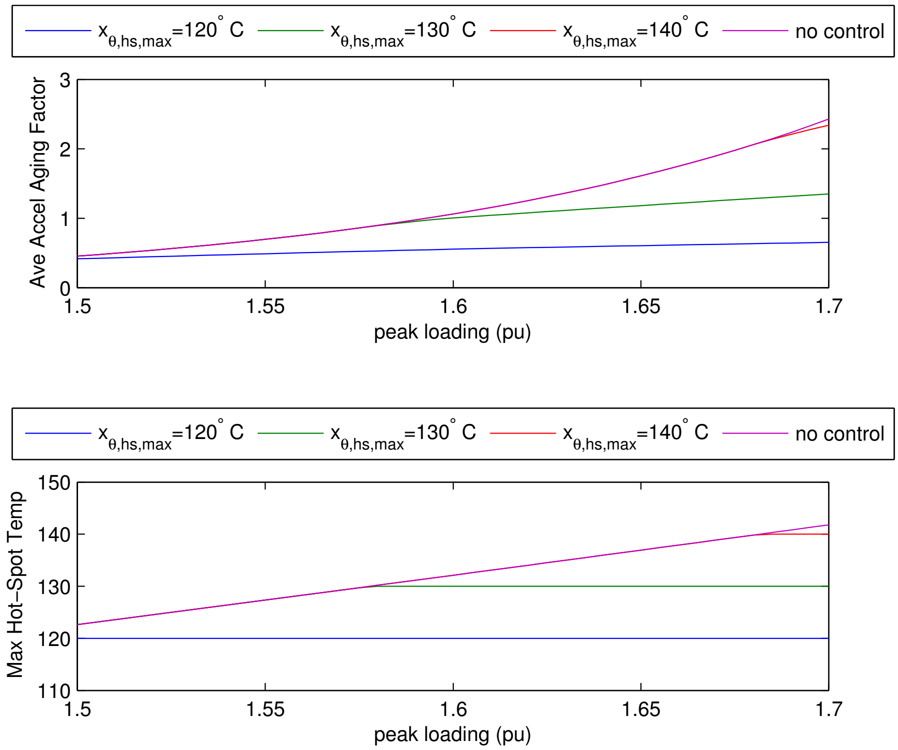

Figure 3.15: Average accelerated aging factor and maximum hot-spot temperature for different loading controls. The average accelerated aging factor and the maximum hot-spot temperature are compiled from a simulation of 1 day. Different scaled load profiles are used for the simulation. Plots are based on the peak values of the profiles used.

3.12 Conclusions

The concept of the intelligent component has been outlined. The model-based optimization framework is developed for intelligent components. The predictive health model within the framework predicts the health state of the equipment. The framework then defines the optimization of management actions based on the predictive health model.

A hierarchical structure of intelligent components was developed. The hierarchy is based on the time scale of management. The planning management having the longest time span is placed at the top, the operational management having the shortest time span is placed at the bottom. The overall problem optimization problem can be divided into simpler and tractable sub problems by using this hierarchical structure. A coordination scheme between other agents is required to solve the global problem. The exchange of information between different levels within the hierarchy of the intelligent components is also proposed. The agents communicate with higher/lower level agents in order to achieve the global goals.

A case study of one layer of intelligent components is presented, which deals with dynamic loading of transformers. It is shown that intelligent components can solve local problems. This concept has been further applied to the optimization of the loading of a transformer. The proposed method optimizes the utilization of the transformer by recommending dynamic load changes when required while keeping the temperature within the safety limits.

Scenarios of availability and absence of predicted loading of the transformer were considered. For the both scenarios the hot-spot temperature was maintained below the allowed limit. For the same prediction horizon, the required load control in case of available predicted loading is less. The case of absence of the predicted loading has the advantage that it is simpler for implementation.

The concept of dynamic loading is more useful when a transformer needs to be loading near or beyond its nominal rating. The dynamic loading of transformer insures that the transformer is loaded optimally without deteriorating its health state beyond an acceptable limit. The approach presented can be applied for any generator, transmission, and distribution transformers. Generator transformers are normally operated at a constant load. Some transmission and distribution transformers could reach to their nominal rating especially during a severe contingency condition. The concept presented in this chapter is particular useful for such cases. Transmission transformers typically have more measurement and monitoring so this concept is easily applicable in such system. There is a general trend towards smart grids in the distribution system as well. This trend could be complemented with advanced control systems, such as the one mentioned in this chapter. With distributed generation, the distribution system will certainly experience more complexity in the future.

Chapter 4

Intelligent networks

This chapter introduces a concept of intelligent networks. An intelligent network consists of distributed interconnected components as described in Chapter 3. These distributed components should solve the global problem of the network such that the network is operated optimally. By collaborating with each other, these intelligent components solve the global problem of the network.

A case study of transformer loading control in a network is presented in this chapter. For the purpose of comparison, a centralized control concept is investigated in Section 4.2. This approach is compared with the proposed distributed approach presented in Section 4.3. The case study of dynamic loading of transformers is introduced in Section 4.4. The case study is used according to the centralized control concept in Section 4.5. The same case study is presented with the distributed approach in Section 4.6. The conclusions of this chapter are presented in Section 4.7.

Parts of this chapter have been published in [35].

4.1 Introduction

An electrical grid consists of a network of generators (power sources) and loads connected by transmission and distribution systems. The energy generated by generators is transferred to the consumers often through complex transmission and distribution networks. These networks are made up of various electrical components such as overhead lines, cables, transformers, switchgears, voltage compensators, etc. The functioning of the network depends on:

- functioning of individual components and their health states,
- interaction between different components.

In order to obtain optimum management of the network, the electrical components should be utilized optimally and the components should communicate with each other in order to find the global optimal operation of the network.

For the optimal management of these components, the concept of intelligent components was proposed in Chapter 3. A model-based optimization framework is developed for the intelligent components. Using this framework, intelligent components can solve their local control problem.

These solutions do not take consideration of the network and other components in the network. Thus, these solutions will be optimal only in the local context. In order to solve a global problem, collaboration between these intelligent components is required.

4.2 Centralized control

A global problem can be solved by a single controller using the model-based optimization. In this case, an optimization problem is defined, which represents the global problem. The model of the whole system is described instead of the model of the component described in previous chapter. The optimization problem can be developed by defining a global optimization function and considering the dynamics of the global system. The optimization problem is formulated as follows:

$$\min_{\mathbf{u}(k),\ldots,\mathbf{u}(k+N-1)} \left[\sum_{l=0}^{N-1} J_{\text{global}}(\mathbf{x}_{\text{global}}(k+l), \mathbf{y}_{\text{global}}(k+l), \mathbf{u}_{\text{global}}(k+l)) \right], \tag{4.1}$$

subject to

$$\begin{aligned} \mathbf{x}_{\text{global}}(k+l+1) &= \mathbf{f}_{\text{global}}(\mathbf{x}_{\text{global}}(k+l), \mathbf{u}_{\text{global}}(k+l)), \\ \mathbf{y}_{\text{global}}(k+l) &= g_{\text{global}}(\mathbf{x}_{\text{global}}(k+l), \mathbf{u}_{\text{global}}(k+l)), \\ \mathbf{h}_{\text{global}}(\mathbf{x}_{\text{global}}(k+l), \mathbf{u}_{\text{global}}(k+l)) &\geq 0, \\ \text{for } l &= 0, \ldots, N-1, \end{aligned}$$

where $\mathbf{x}_{\text{global}}$ are cumulative stresses, $\mathbf{u}_{\text{global}}$ are usages, and $\mathbf{y}_{\text{global}}$ are failure rates of the global system. The function J_{global} is the global optimization function. Dynamic stress models and failure models of the global system are given by $\mathbf{f}_{\text{global}}$ and g_{global}, respectively. The function $\mathbf{h}_{\text{global}}$ represents inequality constraints of the system.

The main disadvantage of the centralized optimization is its complexity due to a large number of states and their dynamics. In most of the cases, some of the states have slower dynamics than others. In such cases, the global states can be categorized into different states based on the rate of their dynamics as follows:

$$\mathbf{x}_{\text{global}} = \begin{bmatrix} \mathbf{x}_{\text{very slow}} \\ \mathbf{x}_{\text{slow}} \\ \mathbf{x}_{\text{fast}} \end{bmatrix}, \tag{4.2}$$

where $\mathbf{x}_{\text{very slow}}$, $\mathbf{x}_{\text{slow}}$, and $\mathbf{x}_{\text{fast}}$ are sets of states of very slow, slow, and fast sub-systems within the global system. These categories are based on relative response times of the dynamics these states.

Corresponding failure rate $\mathbf{y}_{\text{global}}$ and usage $\mathbf{u}_{\text{global}}$ are grouped into following sets of sub-system variables:

$$\mathbf{y}_{\text{global}} = \begin{bmatrix} \mathbf{y}_{\text{very slow}} \\ \mathbf{y}_{\text{slow}} \\ \mathbf{y}_{\text{fast}} \end{bmatrix}, \tag{4.3}$$

where $\mathbf{y}_{\text{very slow}}$, $\mathbf{y}_{\text{slow}}$, and $\mathbf{y}_{\text{fast}}$ are sets of failure rates of very slow, slow, and fast sub-systems within the global system and:

$$\mathbf{u}_{\text{global}} = \begin{bmatrix} \mathbf{u}_{\text{very slow}} \\ \mathbf{u}_{\text{slow}} \\ \mathbf{u}_{\text{fast}} \end{bmatrix}, \tag{4.4}$$

where $\mathbf{u}_{\text{very slow}}$, $\mathbf{u}_{\text{slow}}$, and $\mathbf{u}_{\text{fast}}$ are sets of usages of very slow, slow, and fast sub-systems within the global system.

The dynamics of the decomposed system can be described by a set of differential equations given by:

$$\begin{bmatrix} \dfrac{\mathrm{d}\mathbf{x}_{\text{very slow}}(t)}{\mathrm{d}t} \\ \dfrac{\mathrm{d}\mathbf{x}_{\text{slow}}(t)}{\mathrm{d}t} \\ \dfrac{\mathrm{d}\mathbf{x}_{\text{fast}}(t)}{\mathrm{d}t} \end{bmatrix} = \begin{bmatrix} \mathbf{f}_{\text{very slow}}\left(\mathbf{x}_{\text{very slow}}(t), \mathbf{x}_{\text{slow}}(t), \mathbf{x}_{\text{fast}}(t)\right) \\ \mathbf{f}_{\text{slow}}\left(\mathbf{x}_{\text{very slow}}(t), \mathbf{x}_{\text{slow}}(t), \mathbf{x}_{\text{fast}}(t)\right) \\ \mathbf{f}_{\text{fast}}\left(\mathbf{x}_{\text{very slow}}(t), \mathbf{x}_{\text{slow}}(t), \mathbf{x}_{\text{fast}}(t)\right) \end{bmatrix}, \tag{4.5}$$

where $\mathbf{f}_{\text{very slow}}$, $\mathbf{f}_{\text{slow}}$, and $\mathbf{f}_{\text{fast}}$ are dynamic stress models of very slow, slow, and fast sub-systems, respectively.

Discretization of (4.5) results in:

$$\begin{bmatrix} \mathbf{x}_{\text{very slow}}(k+1) \\ \mathbf{x}_{\text{slow}}(k+1) \\ \mathbf{x}_{\text{fast}}(k+1) \end{bmatrix} = \begin{bmatrix} \mathbf{f}_{\text{very slow}}\left(\mathbf{x}_{\text{very slow}}(k), \mathbf{x}_{\text{slow}}(k), \mathbf{x}_{\text{fast}}(k)\right) \\ \mathbf{f}_{\text{slow}}\left(\mathbf{x}_{\text{very slow}}(k), \mathbf{x}_{\text{slow}}(k), \mathbf{x}_{\text{fast}}(k)\right) \\ \mathbf{f}_{\text{fast}}\left(\mathbf{x}_{\text{very slow}}(k), \mathbf{x}_{\text{slow}}(k), \mathbf{x}_{\text{fast}}(k)\right) \end{bmatrix}. \tag{4.6}$$

The centralized optimization given in (4.1) would be:

$$\min_{\mathbf{u}(k),\ldots,\mathbf{u}(k+N-1)} \left[\sum_{l=0}^{N-1} J_{\text{global}} \begin{pmatrix} \mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l) \\ \mathbf{y}_{\text{very slow}}(k+l), \mathbf{y}_{\text{slow}}(k+l), \mathbf{y}_{\text{fast}}(k+l) \\ \mathbf{u}_{\text{very slow}}(k+l), \mathbf{u}_{\text{slow}}(k+l), \mathbf{u}_{\text{fast}}(k+l) \end{pmatrix} \right], \tag{4.7}$$

subject to

$$\begin{bmatrix} \mathbf{x}_{\text{very slow}}(k+l+1) \\ \mathbf{x}_{\text{slow}}(k+l+1) \\ \mathbf{x}_{\text{fast}}(k+l+1) \end{bmatrix} = \begin{bmatrix} \mathbf{f}_{\text{very slow}}\left(\mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l)\right) \\ \mathbf{f}_{\text{slow}}\left(\mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l)\right) \\ \mathbf{f}_{\text{fast}}\left(\mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l)\right) \end{bmatrix},$$

$$\begin{bmatrix} y_{\text{very slow}}(k+l) \\ y_{\text{slow}}(k+l) \\ y_{\text{fast}}(k+l) \end{bmatrix} = \begin{bmatrix} g_{\text{very slow}} \begin{pmatrix} \mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l), \\ \mathbf{u}_{\text{very slow}}(k+l), \mathbf{u}_{\text{slow}}(k+l), \mathbf{u}_{\text{fast}}(k+l) \end{pmatrix} \\ g_{\text{slow}} \begin{pmatrix} \mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l), \\ \mathbf{u}_{\text{very slow}}(k+l), \mathbf{u}_{\text{slow}}(k+l), \mathbf{u}_{\text{fast}}(k+l) \end{pmatrix} \\ g_{\text{fast}} \begin{pmatrix} \mathbf{x}_{\text{very slow}}(k+l), \mathbf{x}_{\text{slow}}(k+l), \mathbf{x}_{\text{fast}}(k+l), \\ \mathbf{u}_{\text{very slow}}(k+l), \mathbf{u}_{\text{slow}}(k+l), \mathbf{u}_{\text{fast}}(k+l) \end{pmatrix} \end{bmatrix},$$

$$\text{for } l = 0, \ldots, N-1.$$

where $g_{\text{very slow}}$, g_{slow}, and g_{fast} are failure models of very slow, slow, and fast sub-systems, respectively.

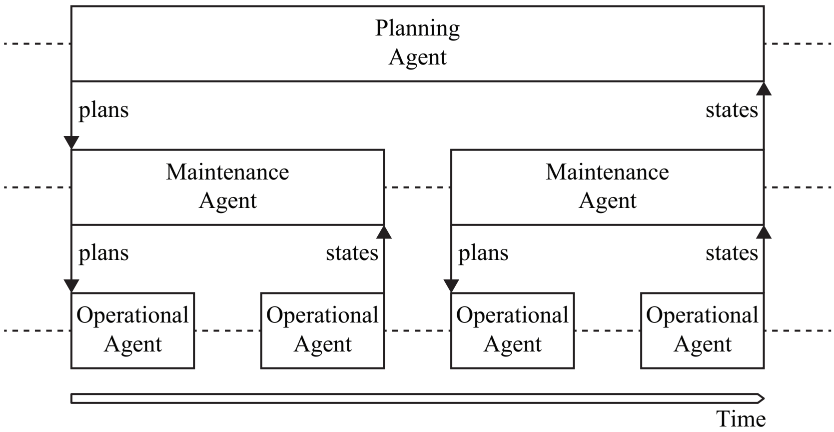

Figure 4.1: Sequence of exchange of plans and states between agents of different hierarchy.

The optimization solution can be decomposed by taking advantage of the time response of different states. A distributed optimization problem can be generated by decomposing the centralized optimization problem based on the dynamics of its states. The distributed control architecture is discussed below.

4.3 Distributed control architectures

In Section 3.4 of Chapter 3, a hierarchical structure of intelligent components was proposed (See Figure 4.1). The intelligent components are controlled by respective management agents based on their local model-based optimizations. The hierarchy of these management agents is based on the notion of time. Generally,

- **lower management agents (operational agents)** control the operation of their components,
- **medium management agents (maintenance agents)** manage maintenance of their components,
- **upper management agents (planning agents)** incorporate planning of their components.

Lower management agents have a faster dynamics, thus a smaller control cycle should be considered for these agents. The control cycles of operational agents typically range from milliseconds to hours [1], whereas the control cycles of maintenance agents varies from hours to years and the control cycle of planning agents may reach up to decades as described in Chapter 1.

Different agents of different management labels would have different sampling times for discritization. Lower management agents (operational agents) would have the shortest sampling times h_{o} due to their fast dynamics. Medium management agents (maintenance agents) would have longer sampling times h_{m}. Upper management agents (planning agents) would have the longest sampling times h_p. The control time steps for these agents would also be different and are denoted by k_o, k_m, and k_p for lower, medium, and upper management agents, respectively.

These differences in their dynamics system time constants can be categorized very slow, slow, and fast dynamics as discussed in Section 4.2. In centralized control described in the previous section, the whole global system is used to develop a single optimization problem. However, this global system can be divided into sub-systems based on their dynamics. For each of these sub-systems, a local optimization problem could be developed. This makes optimization considerably simpler. As a result, local optimization problems can be solved faster than their global problem.

In order to solve a global optimization problem, local optimizations must be coordinated. This coordination is achieved by communication between local optimizations. In the proposed hierarchical system shown in Figure 4.1, operational, maintenance, and planning agents are organized in three layers. Communication between different layers of agents is also depicted in the figure. An agent receives plans from its upper management agents and status of states from its lower management agents. The sequence of exchange of plans and predicted states between agents in different hierarchy is shown in Figure 4.1.

Based on this information, a local optimization problem for the agent can be developed. The global optimization problem described in (4.7) can be decomposed into three local optimization problems. In correspondence with (4.7), the planning agent's dynamics can be considered as very slow dynamics whereas the maintenance agent's dynamics are slow. The operational agents dynamics are fast compared to other agent. The optimization problems of these agents can be described as follows

- **Planning (very slow) agent**

$$\min_{\mathbf{u}(k_\mathrm{p}),\ldots,\mathbf{u}(k_\mathrm{p}+N_\text{very slow}-1)} \left[\sum_{l=0}^{N_\text{very slow}-1} J_\text{very slow} \begin{pmatrix} \mathbf{x}_\text{very slow}(k_\mathrm{p}+l), \\ \mathbf{y}_\text{very slow}(k_\mathrm{p}+l), \\ \mathbf{u}_\text{very slow}(k_\mathrm{p}+l) \end{pmatrix} \right], \tag{4.8}$$

subject to

$$\begin{aligned} \mathbf{x}_\text{very slow}(k_\mathrm{p}+l+1) &= \mathbf{f}_\text{very slow}\left(\mathbf{x}_\text{very slow}(k_\mathrm{p}+l), \mathbf{x}_\text{slow,status}(k_\mathrm{p}+l)\right), \\ y_\text{very slow}(k_\mathrm{p}+l) &= g_\text{very slow}\begin{pmatrix} \mathbf{x}_\text{very slow}(k_\mathrm{p}+l), \mathbf{x}_\text{slow,status}(k_\mathrm{p}+l), \\ \mathbf{u}_\text{very slow}(k_\mathrm{p}+l), \mathbf{u}_\text{slow,status}(k_\mathrm{p}+l) \end{pmatrix}, \\ &\text{for } l = 0,\ldots,N_\text{very slow}-1, \end{aligned}$$

where $N_\text{very slow}$ is the prediction horizon of the local optimization,

- **Maintenance (slow) agent**

$$\min_{\mathbf{u}(k_\mathrm{m}),\ldots,\mathbf{u}(k_\mathrm{m}+N_\text{slow}-1)} \left[\sum_{l=0}^{N_\text{slow}-1} J_\text{slow}\left(\mathbf{x}_\text{slow}(k_\mathrm{m}+l), \mathbf{y}_\text{slow}(k_\mathrm{m}+l), \mathbf{u}_\text{slow}(k_\mathrm{m}+l)\right) \right], \tag{4.9}$$

subject to

$$
\begin{aligned}
\mathbf{x}_{\text{slow}}(k_{\text{m}}+l+1) &= \mathbf{f}_{\text{slow}}\left(\mathbf{x}_{\text{very slow,plan}}(k_{\text{m}}+l), \mathbf{x}_{\text{slow}}(k_{\text{m}}+l), \mathbf{x}_{\text{fast,status}}(k_{\text{m}}+l)\right), \\
y_{\text{slow}}(k_{\text{m}}+l) &= g_{\text{slow}}\begin{pmatrix} \mathbf{x}_{\text{very slow,plan}}(k_{\text{m}}+l), \mathbf{x}_{\text{slow}}(k_{\text{m}}+l), \mathbf{x}_{\text{fast,status}}(k_{\text{m}}+l), \\ \mathbf{u}_{\text{very slow,plan}}(k_{\text{m}}+l), \mathbf{u}_{\text{slow}}(k_{\text{m}}+l), \mathbf{u}_{\text{fast,status}}(k_{\text{m}}+l) \end{pmatrix}, \\
&\text{for } l = 0, \ldots, N_{\text{slow}}-1.
\end{aligned}
$$

where N_{slow} is the prediction horizon of the local optimization,

- **Operational (fast) agent**

$$
\min_{\mathbf{u}(k_{\text{o}}),\ldots,\mathbf{u}(k_{\text{o}}+N_{\text{fast}}-1)} \left[\sum_{l=0}^{N_{\text{fast}}-1} J_{\text{fast}}\left(\mathbf{x}_{\text{fast}}(k_{\text{o}}+l), \mathbf{y}_{\text{fast}}(k_{\text{o}}+l), \mathbf{u}_{\text{fast}}(k_{\text{o}}+l)\right)\right], \tag{4.10}
$$

subject to

$$
\begin{aligned}
\mathbf{x}_{\text{fast}}(k_{\text{o}}+l+1) &= \mathbf{f}_{\text{fast}}\left(\mathbf{x}_{\text{slow,plan}}(k_{\text{o}}+l), \mathbf{x}_{\text{fast,status}}(k_{\text{o}}+l)\right), \\
y_{\text{fast}}(k_{\text{o}}+l) &= g_{\text{fast}}\begin{pmatrix} \mathbf{x}_{\text{slow,plan}}(k_{\text{o}}+l), \mathbf{x}_{\text{fast}}(k_{\text{o}}+l), \\ \mathbf{u}_{\text{slow,plan}}(k_{\text{o}}+l), \mathbf{u}_{\text{fast}}(k_{\text{o}}+l) \end{pmatrix}, \\
&\text{for } l = 0, \ldots, N_{\text{fast}}-1.
\end{aligned}
$$

where N_{fast} is the prediction horizon of the local optimization.

Since the three sub-systems of the agents have different dynamics on the time scale, the sampling time of the discretization of these system would also be different. A slower system can be discretized at a higher sampling time whereas a faster system should be discretized at a shorter sampling time. These three systems could also have a different prediction horizon according to their needs.

4.4 Dynamic loading of transformers in a network

The concept of centralized and distributed control is illustrated with an example of dynamic loading of transformer in a network. The case study is presented in this section.

Dynamic loading of a transformer and its control are presented in Chapter 3. In Chapter 3, loading control of a transformer was assumed to be achieved by external means. This concept is extended in this chapter by considering dynamic loading control of transformers within a network. In this chapter, we include the loading control as well.

Control of transformer loading can be done by redirecting the load flow of the network. Thus, this problem consists of two levels of control, namely:

- Control of hot-spot temperatures of transformers by changing their loading,
- Control of loading of transformers by changing settings of the network elements which affect power flow within the network.

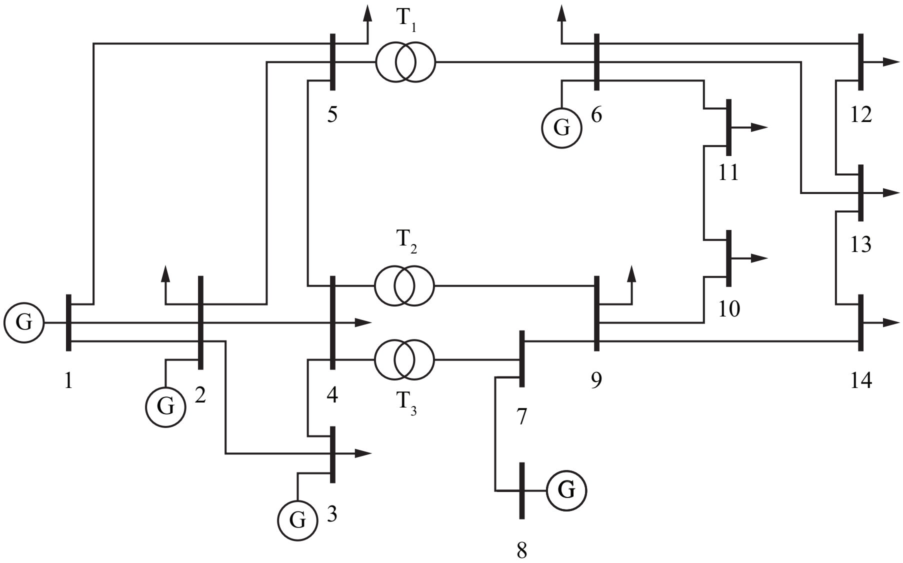

Figure 4.2: IEEE 14 bus network [36] used for the case study. The network consists of three transformers.

In order to control hot-spot temperatures of transformers, their thermal models are required. For the control of transformers' loading, a power flow model of the network is required. These two concept controls are implemented using the centralized as well as the distributed control approaches presented in Sections 4.2 and 4.3, respectively. In the centralized control scheme, both the thermal and the power flow problems are defined in one central optimization problem, whereas in the distributed control approach a two-level hierarchy is developed.

4.4.1 IEEE 14 bus network

The IEEE 14 bus system [36] is chosen for the case study. The IEEE 14 bus network, illustrated in Figure 4.2, includes transmission and distribution systems. The network consists of three transformers T_1, T_2, and T_3. Transformers T_1 and T_2 are two winding transformers. Transformer T_3 is a three winding transformer. In the network, re-routing of power flow through these transformers is possible. Power flow re-routing between two parallel transformers T_2 and T_3 is possible. In addition, power flow re-routing between the set of parallel transformers (T_2 and T_3) and transformer T_1 can be achieved. Power flow control (re-routing of power) can be accomplished by:

- Controlling real and reactive power of generators,
- Controlling real and reactive power of loads,
- Changing tap positions of transformers.

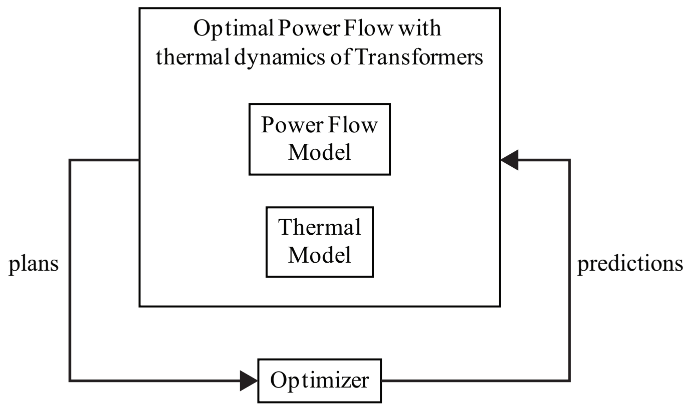

Figure 4.3: Centralized control of dynamic loading of transformer. In this scheme, the thermal model along with the power flow model are considered in the global optimization problem.

Three generators are considered at busses 1, 2, and 3. Two reactive power compensators are located at busses 6 and 8. All the real and reactive power generations are considered controllable. The loads of the distribution system are also assumed to be controllable. Load shedding is allowed at busses 6, 9, 10, 11, 12, 13, and 14.

Data of the network parameters and the limits of the active and the reactive power generation are provided by [36] and are listed in Appendix C. The cost of generation and the cost of load shedding are also given in Appendix C. The acceptable limit of voltage variation in the busses is considered to be $\pm 6\%$.

The nominal ratings of transformers T_1, T_2, and T_3 are considered to be 50 MVA, 17 MVA, and 40 MVA, respectively. The thermal model parameters of transformers are taken from corresponding parameters of medium and large power transformers (with ONAN cooling type) given in [26] and are listed in Appendix D.

For the simulation purposes, a constant ambient temperature of 25°C is considered. In order to emphasize the control of the loading of transformers, the power flow in the network is not considered to be constrained by the loading capacities of the transmission and distribution lines. In order words, the loading capacities of the transformers are considered to be the bottlenecks in the network [36].

4.5 Centralized control of dynamic loading of transformers in a network

In a centralized control scheme the global problem of dynamic loading of transformers in a network is considered as a whole. The global problem consists of thermal and power flow models. The optimization scheme is depicted in Figure 4.3. As illustrated in the figure, one single optimizer is used and one global optimization function is defined. This optimizer uses predictions from both the thermal as well as the power flow model.

4.5.1 Optimal power flow of the network with the dynamics of the hot-spot and top-oil temperatures

Typically, the loading limits of transformers in a network are set at constant levels by the manufacturers and/or utilities. However, the maximum allowable loading of a transformer mainly depends on the thermal limits of the transformer. The hot-spot temperature of the transformer can be used to determine the maximum allowable loading. In this section, normal life expectancy loading defined in IEEE C57.91 [27] is considered. The maximum hot-spot temperature allowed for this type of loading is 120°C.

The predictive health model described in Section 3.7 is used to predict the hot-spot temperature $x_{\theta,\mathrm{hs}}$. The predicted hot-spot temperature has to be maintained below the allowed limit by controlling the transformers' loading u_{I}. The transformers' loading u_{I} can be controlled by controlling the active and reactive power of generators and loads. The loading u_{I} can also be controlled by:

- Active and reactive power generation,
- Load control (shedding or transfer of loads),
- The tap position of transformers.

In order to determine the optimal control inputs, an optimal power flow (OPF) of the network is calculated. The dynamics of the top-oil temperature (3.14) and the hot-spot temperature (3.17) are considered in this OPF. The dynamic OPF problem is formulated as follows:

$$\min_{\alpha,\mathbf{u}(k),\ldots,\mathbf{u}(k+N-1)} \sum_{l=0}^{N-1} J_{\mathrm{total}}\left(\mathbf{x}(k+l+1),\mathbf{z}(k+l),\mathbf{u}(k+l)\right), \tag{4.11}$$

subject to

$$\begin{aligned}
\mathbf{x}(k+l+1) &= \mathbf{f}_{\mathrm{th}}\left((\mathbf{x}(k+l),\mathbf{z}(k+l),\mathbf{u}(k+l)\right), \\
\mathbf{g}_{\mathrm{pf}}\left((\mathbf{x}(k+l+1),\mathbf{z}(k+l),\mathbf{u}(k+l)\right) &= 0, \\
\mathbf{h}_{\mathrm{pf}}\left((\mathbf{x}(k+l+1),\mathbf{z}(k+l),\mathbf{u}(k+l)\right) &\leq 0, \\
&\text{for } l = 0,\ldots,N-1.
\end{aligned}$$

The OPF is considered for a prediction horizon of N steps in the future. The three sets of variables considered in the OPF [37] are:

- The algebraic state vector $\mathbf{z}$ includes the variables for which no dynamics are considered,
$$\mathbf{z} = \left[z_{\theta}^{i_{\mathrm{b},1}}, z_{\mathrm{v}}^{i_{\mathrm{b},1}}, \ldots, z_{\theta}^{i_{\mathrm{b},n}}, z_{\mathrm{v}}^{i_{\mathrm{b},n}}\right]^{\mathrm{T}}, \tag{4.12}$$
with $\mathcal{I}_{\mathrm{b}} = \{i_{\mathrm{b},1},\ldots,i_{\mathrm{b},n}\}$ the set of indices of busses in the network, where z_{θ}^{i} and z_{v}^{i} are the angle and the voltage magnitude of bus i, respectively. The dynamics for these variables are neglected because they are too fast compared to the dynamics of the hot-spot temperature and the top-oil temperature.

- The dynamic state vector $\mathbf{x}$ includes the variables for which dynamics are defined,

$$\mathbf{x} = \left[x_{\theta,\text{oil}}^{i_{\text{t},1}}, x_{\theta,\text{hs}}^{i_{\text{t},1}}, \ldots, x_{\theta,\text{oil}}^{i_{\text{t,n}}}, x_{\theta,\text{hs}}^{i_{\text{t,n}}}\right]^{\text{T}}, \tag{4.13}$$

  with $\mathcal{I}_{\text{t}} = \{i_{\text{t},1}, \ldots, i_{\text{t},n}\}$ the set of indices of transformers in the network, where $x_{\theta,\text{oil}}^{i}$ and $x_{\theta,\text{hs}}^{i}$ are the top-oil temperature and the hot-spot temperature of transformer i, respectively.

- The control vector $\mathbf{u}$ consists of the control inputs of the network,

$$\mathbf{u} = \left[u_{\text{P,gen}}^{i_{\text{g},1}}, u_{\text{Q,gen}}^{i_{\text{g},1}}, u_{\text{tap}}^{i_{\text{t},1}}, u_{\text{shed}}^{i_{\text{l},1}}, \ldots, u_{\text{P,gen}}^{i_{\text{g},n}}, u_{\text{Q,gen}}^{i_{\text{g},n}}, u_{\text{tap}}^{i_{\text{t},n}}, u_{\text{shed}}^{i_{\text{l},n}}\right]^{\text{T}}, \tag{4.14}$$

  with $\mathcal{I}_{\text{g}} = \left\{i_{\text{g},1}, \ldots, i_{\text{g},n}\right\}$ the set of indices of generators in the network, $\mathcal{I}_{\text{t}} = \{i_{\text{t},1}, \ldots, i_{\text{t},n}\}$ the set of indices of transformers in the network, and $\mathcal{I}_{\text{l}} = \{i_{\text{l},1}, \ldots, i_{\text{l},n}\}$ the set of indices of loads in the network, where $u_{\text{P,gen}}^{i}$ and $u_{\text{Q,gen}}^{i}$ are the active and the reactive power generation at bus i, u_{tap}^{i} is the tap position of transformer i, and u_{shed}^{i} is the shedding of the load at bus i. Shedding of the active and the reactive loads is given by:

$$\begin{gathered} P_{\text{load,actual}}^{i}(k) = \left(1 - u_{\text{shed}}^{i}(k)\right) P_{\text{load,demand}}^{i}(k) \\ Q_{\text{load,actual}}^{i}(k) = \left(1 - u_{\text{shed}}^{i}(k)\right) Q_{\text{load,demand}}^{i}(k) \\ \text{for } 0 \leq u_{\text{shed}}^{i}(k) \leq 1, \end{gathered}$$

  where $P_{\text{load,demand}}^{i}$ and $Q_{\text{load,demand}}^{i}$ are the real power and the reactive power demand at bus i, respectively, and where $P_{\text{load,actual}}^{i}$ and $Q_{\text{load,actual}}^{i}$ are the real power and the reactive power delivered at bus i, respectively.

Nodal power balances between the nodes in the network $\mathbf{g}_{\text{pf}}$ are considered as constraints for the optimization. The predictive health model $\mathbf{f}_{\text{th}}$, which describes the dynamics of the top oil temperature (3.14) and the hot-spot temperature (3.17), are constraints of the optimization problem. The branch flow limits are given by $\mathbf{h}_{\text{pf}}$. For transformers, the maximum hot-spot temperature limit is given by:

$$x_{\theta,\text{hs}}^{i}(k+1) \leq x_{\theta,\text{hs}}^{\max}, \tag{4.15}$$

where $x_{\theta,\text{hs}}^{\max}$ is maximum hot-spot temperature limit of transformer i.

Allowable voltage magnitudes in the network are taken into account by the variable limits given by:

$$z_{\text{v,min}}^{i} \leq z_{\text{v}}^{i}(k) \leq z_{\text{v,max}}^{i}, \tag{4.16}$$

where $z_{\text{v,min}}^{i}$ and $z_{\text{v,max}}^{i}$ are minimum and maximum voltage limits at bus i, respectively.

Maximum and minimum generation capacities of generators are also considered in the variable limit given by:

$$\begin{aligned} u^i_{\mathrm{P,gen,min}} \leq u^i_{\mathrm{P,gen}}(k) \leq u^i_{\mathrm{P,gen,max}}, \\ u^i_{\mathrm{Q,gen,min}} \leq u^i_{\mathrm{Q,gen}}(k) \leq u^i_{\mathrm{Q,gen,max}} \end{aligned}, \tag{4.17}$$

where $u^i_{\mathrm{P,gen,min}}$ and $u^i_{\mathrm{P,gen,max}}$ are minimum and maximum active power generation limit of generator at bus i, respectively. $u^i_{\mathrm{Q,gen,min}}$ and $u^i_{\mathrm{Q,gen,max}}$ are minimum and maximum reactive power generation limit of generator at bus i, respectively.

The total cost function over the prediction horizon N is given by:

$$\begin{aligned} \sum_{l=0}^{N-1} J_{\mathrm{total}}\left(\mathbf{x}(k+l+1), \mathbf{z}(k+l), \mathbf{u}(k+l)\right) = \sum_{l=0}^{N-1} J_{\mathrm{gen}}\left(u^i_{\mathrm{P,gen}}(k+l), u^i_{\mathrm{Q,gen}}(k+l)\right) \\ + J_{\mathrm{tap}}\left(u^i_{\mathrm{tap}}(k+l)\right) + J_{\mathrm{shed}}\left(u^i_{\mathrm{shed}}(k+l)\right), \end{aligned} \tag{4.18}$$

where J_{gen}, J_{tap}, and J_{shed} give the cost of generation, the cost of tap and the cost of load shedding, respectively.

The cost of generation J_{gen} is given by:

$$J_{\mathrm{gen}}\left(u^i_{\mathrm{P,gen}}(k), u^i_{\mathrm{Q,gen}}(k)\right) = C^i_1 u^i_{\mathrm{P,gen}}(k) + C^i_2 \left(u^i_{\mathrm{P,gen}}(k)\right)^2,$$

where $C^1_1 = 20$, $C^2_1 = 20$, $C^3_1 = 20$, $C^6_1 = 40$, $C^8_1 = 40$, $C^1_2 = 0.043$, $C^2_2 = 0.25$, $C^3_2 = 0.01$, $C^6_2 = 0.01$, and $C^8_2 = 0.01$ [36].

The cost of tap changes is given by:

$$J_{\mathrm{tap}}\left(u^i_{\mathrm{tap}}(k)\right) = \left(u^i_{\mathrm{tap}}(k)\right)^2.$$

The cost of shedding is chosen to be higher than the cost of generation to avoid shedding as much as possible. The cost of shedding J_{shed} is given by:

$$J_{\mathrm{shed}}\left(u^i_{\mathrm{shed}}(k)\right) = D_1 u^i_{\mathrm{shed}}(k) P^i_{\mathrm{load}}(k) + D_2 \left(u^i_{\mathrm{shed}}(k) P^i_{\mathrm{load}}(k)\right)^2,$$

where $D_1 = 80$ and $D_2 = 0.5$[36].

4.5.2 Simulation

The optimal power flow computation for a typical load profile is calculated. A step time h of 1 minute is considered. A prediction horizon N of 15 steps is chosen such that the optimization is performed for a prediction horizon time of 15 minutes. Figure 4.4 gives the load demands (in dashed lines) and the actual loads (in solid lines) at different distribution busses. The hot-spot temperature and the top-oil temperature of three transformers are presented in Figure 4.5. The loadings of three transformers are shown in Figure 4.6. The hot-spot temperatures correspond to the loadings of the transformers.

As illustrated in Figure 4.5, the hot-spot temperature of transformer T_2 reaches the maximum limit of 120°C at $k = 169$. Transformer T_2 could not be loaded beyond this point as it would be thermally overloaded the transformer. The loading of transformer T_2 is controlled in such a way that its hot-spot temperature does not exceed the limit. The loading control

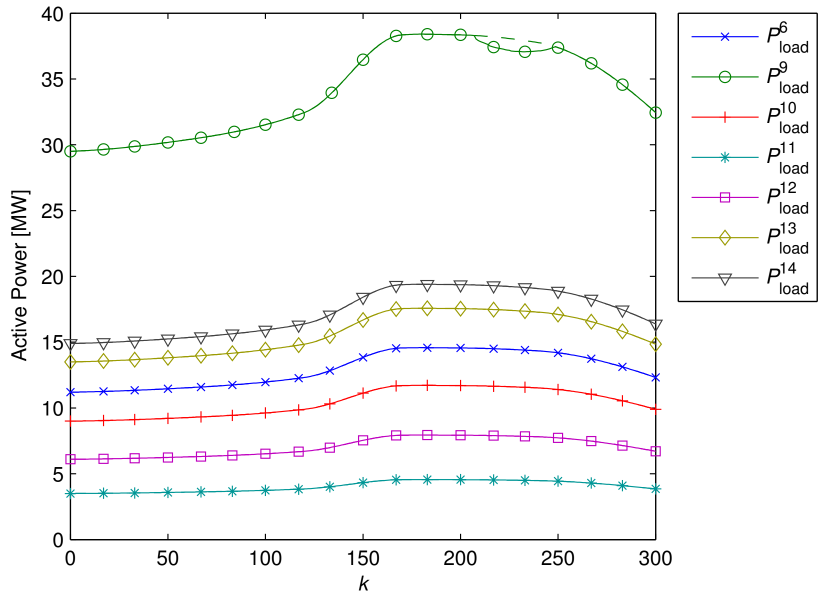

Figure 4.4: Demand of the real power (dashed lines) and actual real power delivered (solid lines) at busses of the distribution system.

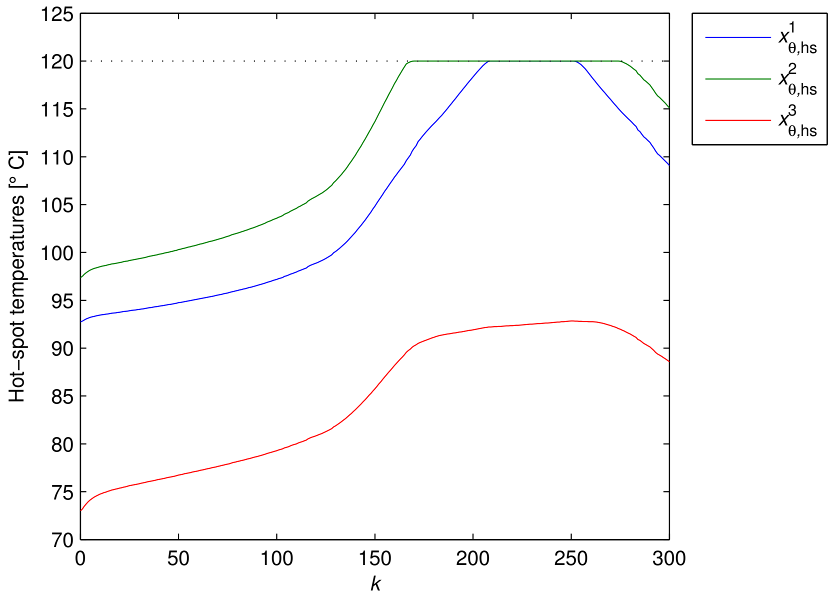

Figure 4.5: Hot-spot and top-oil temperatures of transformers T_1, T_2, *and* T_3.

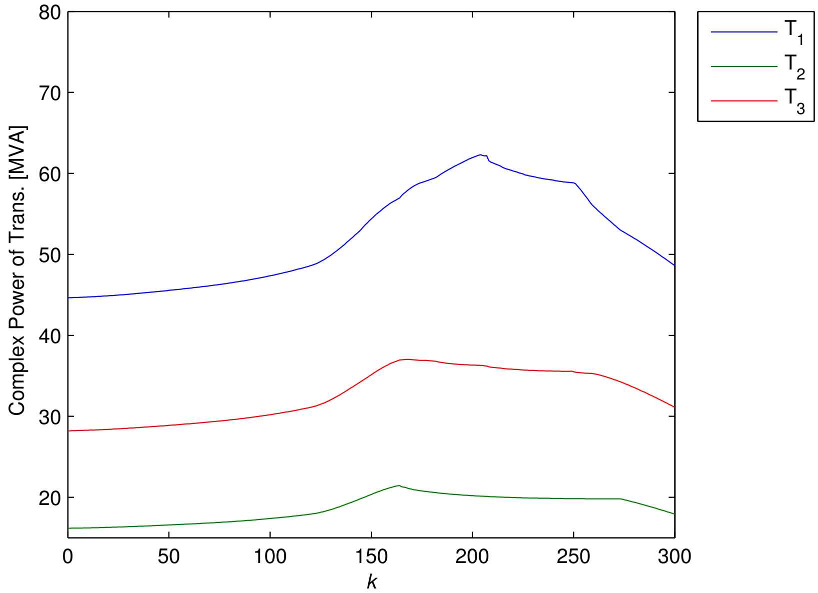

Figure 4.6: Loading of three transformers in the network.

is achieved by controlling the generations and tap positions of transformers in the network. At this point, loads are not shed.

At $k = 207$, the hot-spot temperature of transformer T_1 also reaches the thermal limit. As the hot-spot temperature of transformers T_1 and T_2 reaches the thermal limit, the power flow cannot be controlled with the generation control and the tap control. As a result, the shedding of load at bus 9 starts. As seen in Figure 4.4, the actual load (solid line) is less than the load demand (dotted line) for range of k between time steps 207 and 252.

After time step 252, the load demands decrease, which results in a reduction of the hot-spot temperature of transformer T_1. From this point on, transformer T_1 is loaded below to its thermal limit. As a result, some of the loading of transformer T_2 can be transferred to transformer T_1. Hence, the power flow can be controlled by generation control and tap control. Thus, shedding is eliminated.

In this simulation, the hot-spot prediction is used for determining the loading limits of transformers in a network. The loading of the transformers is controlled by changing the active and the reactive power generation and the tap setting of the transformers. The shedding of the load is done when the loading of the transformer cannot be limited by controlling the generation and the tap settings anymore. The hot-spot temperatures of the transformers are maintained below the maximum allowed limit.

4.5.3 Disadvantage of the centralized control approach

In the centralized control approach presented in this section, the control actions are derived by solving one single global optimization problem given in (4.11). This global optimization

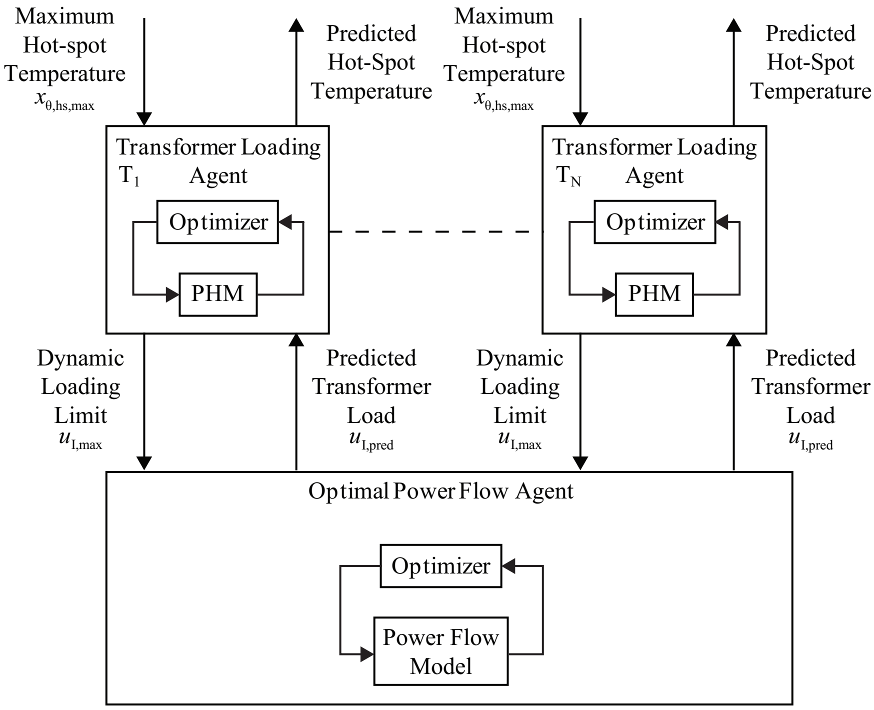

Figure 4.7: Distributed control of dynamic loading of transformer.

problem becomes larger as the size of the network increases. In addition, an increase in the number of transformers in the network also increases the complexity of the optimization problem. For a larger network, the complex optimization problem will be difficult to solve and takes a lot of computation time. In order to reduce the complexity, a distributed approach can be used. This approach is presented in the next section.

4.6 Distributed control of dynamic loading of transformers in a network

In the centralized control approach (Section 4.5), the thermal model and the power flow model are combined into one global model. In the distributed control approach, these two model are kept separate and put into a hierarchical control system which has been developed and is shown in Figure 4.7. The upper level consists of the Transformer Loading Agent and the lower level is the Optimal Power Flow Agent. The thermal model of transformer is included in the Transformer Loading Agent while the Optimal Power Flow Agent takes care of the optimal power flow problem. The Transformer Loading Agent sends dynamic loading limits to the Power Flow Agent which in turn updates the predicted transformer loading.

The IEEE 14 bus network consists of three transformers, thus there are three Transformer Loading Agents in this case. These Transformer Loading Agents interact with an

Optimal Power Flow Agent which controls the network according to the limits set by the three Transformer Loading Agents.

4.6.1 Transformer Loading Agent

The Transformer Loading Agent has been developed in Chapter 3. In Chapter 3, two control algorithms of dynamic loading were discussed which are:

1. **Section 3.8.1: Dynamic loading based on predicted loading** which provides dynamic loading limits to the Optimal Power Flow Agent, based on the predicted loading of the transformer,
2. **Section 3.8.2: Dynamic loading in absence of predicted loading** which does not know the predicted loading but provides a dynamic loading limit based on the state of the transformer.

The first algorithm is used in this case study as it receives predicted loading from Optimal Power Flow Agent. The optimization problem of Transformer Loading Agent is given in (3.18) of Chapter 3. This optimization problem is reiterated as:

$$\min_{\alpha, u_{\mathrm{I,max}}(k_{\mathrm{th}}),\ldots,u_{\mathrm{I,max}}(k_{\mathrm{th}}+N_{\mathrm{th}}-1)} \sum_{l=0}^{N_{\mathrm{th}}-1} \left[c_1 \left(u_{\mathrm{I,max}}(k_{\mathrm{th}}+l) - \alpha u_{\mathrm{I,pred}}(k_{\mathrm{th}}+l) \right)^2 \right] - c_2\alpha, \tag{4.19}$$

subject to

$$\begin{aligned}
x_{\theta,\mathrm{oil}}(k_{\mathrm{th}}+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k_{\mathrm{th}}+l), u_{\theta,\mathrm{amb}}(k_{\mathrm{th}}+l), u_{\mathrm{I,max}}(k_{\mathrm{th}}+l)),\\
x_{\theta,\mathrm{hs}}(k_{\mathrm{th}}+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k_{\mathrm{th}}+l), x_{\theta,\mathrm{oil}}(k_{\mathrm{th}}+l), u_{\mathrm{I,max}}(k_{\mathrm{th}}+l)),\\
x_{\theta,\mathrm{hs}}(k_{\mathrm{th}}+l+1) &\leq x_{\theta,\mathrm{hs,max}},\\
\alpha &\geq 1,\\
&\text{for } l = 0,\ldots,N_{\mathrm{th}}-1,
\end{aligned}$$

where k_{th} denotes the control time step of the Transformer Loading Agent N_{th} denotes the prediction horizon of the Transformer Loading Agent.

The Transformer Agent receives the predicted transformer loading of transformer $u_{\mathrm{I,pred}}$ from the Optimal Power Flow Agent. Then the Transformer agent determines the maximum loading of transformer limit $u_{\mathrm{I,max}}$ and sends the limit to the Optimal Power Flow Agent.

4.6.2 Optimal Power Flow Agent

The Optimal Power Flow Agent is similar to the classical optimal power flow problem. Loading limits of transformers in the network are dynamically set by their Transformer Loading Agents. The optimization problem is a simplified version of (4.11) since the thermal dynamics are not included in it. The Optimal Power Flow Agent does not have any dynamics since it does not have any differential equations. The power flow is a set steady state model described by a set of algebraic equations so it does not depend on the result of the past (previous iterations). Thus, the optimal power flow could be solved without any predictions. Thus no prediction horizon is considered for Optimal Power Flow Agent.

The optimization problem of the Optimal Power Flow Agent is:

$$\min_{\mathbf{u}(k_{\mathrm{opf}})} J_{\mathrm{total}}\left(\mathbf{z}(k_{\mathrm{opf}}), \mathbf{u}(k_{\mathrm{opf}})\right), \tag{4.20}$$

subject to

$$\mathbf{g}_{\mathrm{pf}}\left((\mathbf{z}(k_{\mathrm{opf}}), \mathbf{u}(k_{\mathrm{opf}})\right) = 0,$$
$$\mathbf{h}_{\mathrm{pf}}\left((\mathbf{z}(k_{\mathrm{opf}}), \mathbf{u}(k_{\mathrm{opf}})\right) \leq 0,$$

where k_{opf} is the control time step of Optimal Power Flow Agent.

The maximum loading limit of the transformer $u_{\mathrm{I,max}}$, provided by Transformer Loading Agent, is considered as a branch flow limit function $\mathbf{h}_{\mathrm{pf}}$. The branch flow limit is defined for all the transformers in the network, as their Transformer Loading Agent will provide their dynamic loading limit. The branch flow limit function $\mathbf{h}_{\mathrm{pf}}$ is redefined as:

$$\mathbf{u}_{\mathrm{I,t}}(k_{\mathrm{opf}}) - \mathbf{u}_{\mathrm{I,max,t}}(k_{\mathrm{opf}}) \leq 0; \tag{4.21}$$

where the variables are defined as follows:

- the set of loadings of transformer are given by $\mathbf{u}_{\mathrm{I,t}}$ such that,

$$\mathbf{u}_{\mathrm{I,t}} = \left[u_{\mathrm{I,t}}^{i_{\mathrm{t,1}}}, \cdots, u_{\mathrm{I,t}}^{i_{\mathrm{t,n}}}\right], \tag{4.22}$$

  with $\mathcal{I}_{\mathrm{t}} = \{i_{\mathrm{t},1}, \ldots, i_{\mathrm{t},n}\}$ being a set of indices of transformers in the network and $u_{\mathrm{I,t}}^{i}$ the loadings of these transformers,

- the set of loadings of transformer are given by $\mathbf{u}_{\mathrm{I,t}}$ such that,

$$\mathbf{u}_{\mathrm{I,t,max}} = \left[u_{\mathrm{I,t,max}}^{i_{\mathrm{t,1}}}, \cdots, u_{\mathrm{I,t,max}}^{i_{\mathrm{t,n}}}\right], \tag{4.23}$$

  with $\mathcal{I}_{\mathrm{t}} = \{i_{\mathrm{t},1}, \ldots, i_{\mathrm{t},n}\}$ being a set of indices of transformers in the network and $u_{\mathrm{I,t,max}}^{i}$ the loading limits of these transformers.

These loading limits of transformers $u_{\mathrm{I,t,max}}^{i}$ are provided by their corresponding Transformer Loading Agents. The predicted loadings for transformers in the network are calculated by their Optimal Power Flow Agents based on their predicted load curves.

4.6.3 Simulation

The distributed control approach is simulated with the same load profile used as in the previous case of centralized control (Section 4.5). Again, a step time h of 1 minute is considered for the Transformer Loading Agents and the Optimal Power Flow Agent. The prediction horizon for the Transformer Loading Agent N_{th} of 15 steps is chosen, which is same as in the case of centralized control. The optimal load flow is executed at an interval of 1 minute.

The simulation results are presented in Figures 4.8, 4.9, and 4.10. Figure 4.8 shows the load demands (in dashed lines) and the actual loads (in solid lines) at different distribution busses. The hot-spot temperature and the top-oil temperature of three transformers are

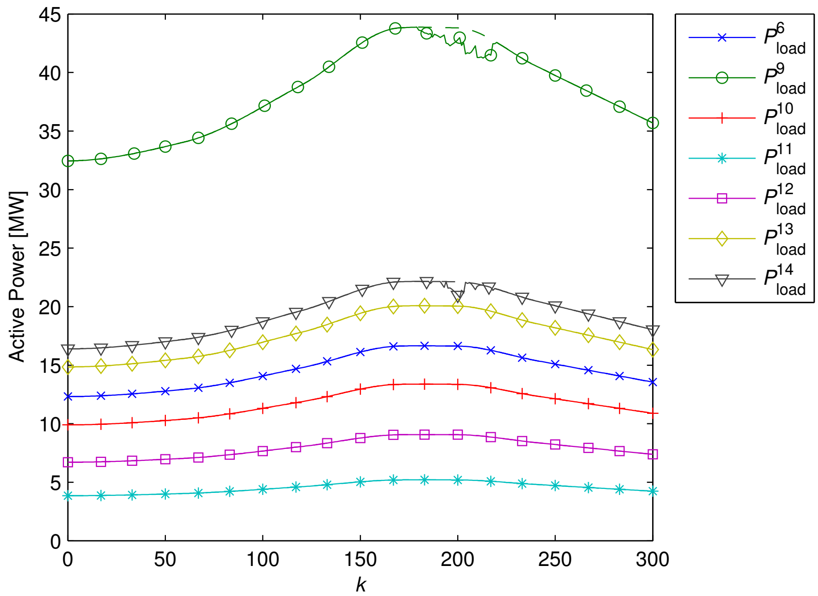

Figure 4.8: Demand of the real power (dashed lines) and actual real power delivered (solid lines) at busses of the distribution system.

presented in Figure 4.5. Figure 4.10 gives the loading of three transformers. The maximum loading limits provided by the Transformer Loading Agents are shown as dashed lines in this figure.

The simulation plots are similar to the simulation plots of the centralized control approach. At $k = 165$, the hot-spot temperature of transformer T_2 reaches the maximum limit of 120°C (see Figure 4.9). As in the centralized control approach, the loading of the thermally overloading transformer is re-routed through other transformers, thus the shedding of the loads is avoided.

At $k = 179$, the hot-spot temperature of transformer T_1 also reaches the limit. Since both the transformers are at their thermal overload point, the network sheds some of their loads at bus 9 and bus 14 (see Figure 4.8 at t $k = 179$).

After time step 220, no further load shedding is required, since the hot-spot temperature of transformer T_1 drops below the maximum limit.

The interaction of Transformer Loading and Optimal Power Flow agents can be seen in Figure 4.10. The actual loadings of transformers u_I are given by solid lines and are controlled by the Optimal Power Flow Agent. The maximum loading limits of transformers are also plotted in the figure (dashed lines). These limits are provided by these three Transformer Loading Agents. The Optimal Power Flow Agent respects the maximum limit and controls the network such that the actual loadings remain below the maximum limits.

Another interesting factor in this figure is the dynamic change of the maximum loading limits. These limits are based on the thermal statuses of transformers. Initially, transformers are lightly loaded which results in lower hot-spot temperature. This gives a higher maxi-

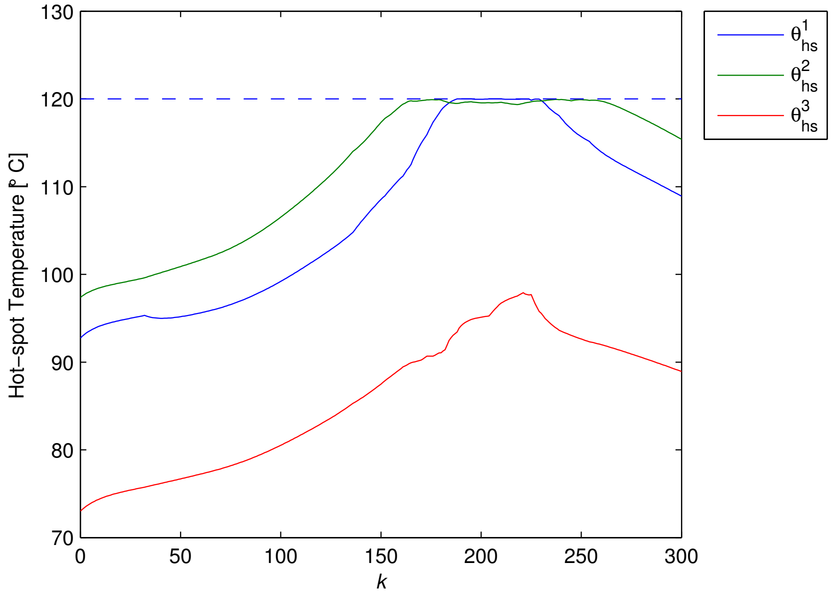

Figure 4.9: Hot-spot and top-oil temperatures of transformers T_1, T_2, *and* T_3.

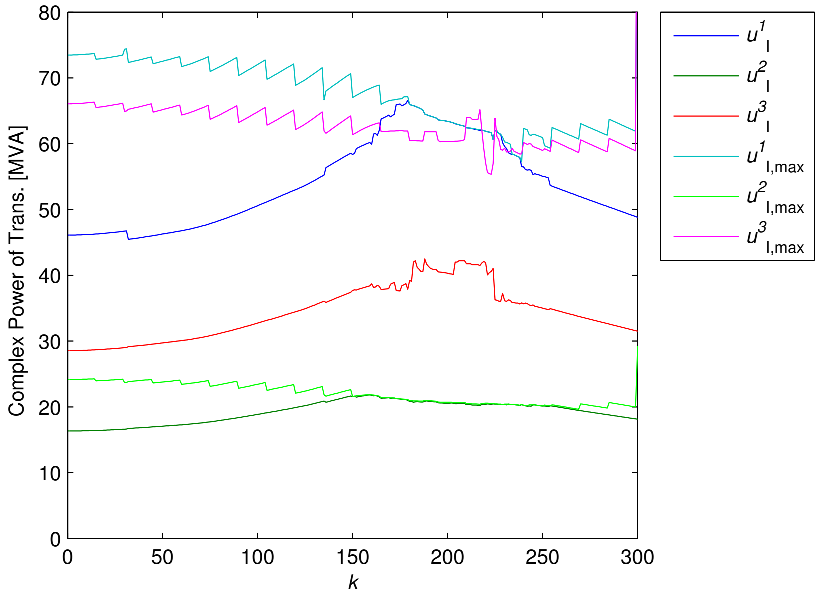

Figure 4.10: Maximum loading limits (dashed lines) and actual loadings (solid lines) of three transformers in the network.

mum loading limits. As the transformer loadings increase, their hot-spot temperatures also increase. This results in a reduction of the maximum loading limits. When the hot-spot temperatures reach their maximum limits, transformers are loaded to their maximum thermal capacity. In these periods, the actual loadings of transformers are equal to their maximum loading limits.

This simulation shows the coordination between Transformer Loading Agents and Optimal Power Flow Agent. With this coordination, the hot-spot temperatures are maintained below the acceptable limit.

4.7 Conclusions

In this chapter, the centralized control approach is presented in which a global optimization problem can be developed. Such a centralized control approach tends to become complex and difficult to solve as the size of the network and the number of their components increase. To solve this problem, a distributed control approach is presented. This distributed control architecture is built around the hierarchy structure presented in Chapter 3. This approach decomposes the complex global problem into various local problems. By using the distributed approach, the complex problem of centralized approach is simplified considerably.

As in the centralized case, the goal of distributed approach is also to solve the global problem. In order to achieve this goal, the decomposed local problems should be coordinated. The agent approach is suitable for this purpose, as the agents can effectively communicate with each other in order to solve the global problem. By collaboration of agents, the distributed control system is able to control the system.

A distributed control of loading of transformers in a network is also presented as a case study. This case study is solved using centralized control approach for comparison. The result of the case study shows that the distributed approach is able to solve the global problem more efficiently. In addition, the distributed approach is considerably more tractable than the centralized approach.

In the case study, the transformer loading is controlled by controlling transformer taps, generation, and load. With the distributed control (as well as centralized control) the hot-spot temperature is maintained within an acceptable limit. This way, transformers are safely loaded up to their maximum limits.

The hierarchical distributed structure also gives a modular approach to the system. One of the agents (such as the transformer loading) could easily be modified to incorporate different needs whereas the design of control of the rest of the agents is not required to be changed.

Chapter 5

Information interface support

In Chapter 2, the concept of intelligent agents was proposed, which provides a distributed approach of solving complex problems. In order to achieve distributed control, communication between the agents is essential. Moreover, the information of the grid is maintained in different systems with their own proprietary information formats. In order to effectively exchange information between these systems, a common information interface support is required. This chapter proposes a common information interface which could be used in the intelligent grid concept.

A background of the information in the grid is presented in Section 5.1. The types of information used in the electricity grid is elaborated in Section 5.2. The utilization of the various information in the grid is presented in Section 5.3. In order to meet the needs of the information use of the grid a common information platform is needed. The common information model presently used in the electricity grid is introduced in Section 5.4. The common information model is extended in order to fulfill the needs of the future grid, which is discussed in Section 5.5. Based on the proposed extension, modeling of management of grid assets is illustrated in Section 5.6. The dynamic loading of transformers, described in Chapter 4, is presented as a CIM extension in Section 5.7.

Parts of this chapter have been published in [38] and [39].

5.1 Introduction

The electricity grid is evolving due to recent technological developments to introduce more intelligence in the assets. Because of the advancement in measurement techniques and sensor technologies, a significant amount of technical information about the assets in the grid has become available. Various online and offline condition monitoring systems have been developed for different types of equipments. This technical information together with economical and societal information is very important for the decision making process for asset management of the grid [6]. Economical information includes cost and optimal usage of equipment and societal information includes effects of the electrical system to the society such as outage.

Asset management balances cost, performance, and risk of the utilities by planning the future actions based on historical and measured data [5]. Information processing is a key

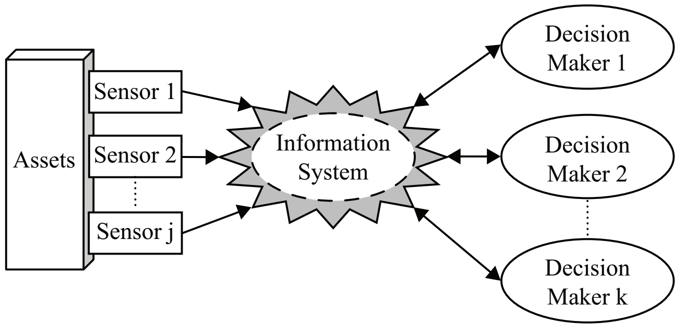

Figure 5.1: Information gap between information sources and information users in the electricity grid.

factor for the optimization of asset performance. The available information is processed with a number of analysis tools, such as data mining systems. The processed data is then used by the decision makers to make the operational, maintenance, and planning decisions [1]. With developments in the asset management system of the electricity grid, information is shared between different platforms with different types of information systems [1].

In addition, the intelligent agent concept introduced in Chapter 2 enables distributed control of the grid. In such a distributed approach, communication between these agents is indispensable for the control of the network. These agents are embedded with systems built in different platforms.

With the increase of cross platform information exchange, an effective information system is often lacking in the electrical grid. This information gap between the newly developed sensors and the decision makers is illustrated in Figure 5.1.

In order to effectively implement the intelligent agent concept in the utilities, a reliable and error-free information exchange between different units within the utility is required. A common information interface is required to effectively bridge the different information systems and protocols. Architecture of such a common information interface is presented in this chapter. The information from different systems can be converted to a common format by using an adapter. The adapter can also be used to translate the information in the common information interface format to other relevant data formats of different systems.

By using the proposed common information interface, a standard format of information exchange can be developed, which can be used for the cross platform information exchange. System integration with components from different vendors is also possible with information exchange via the adapter.

Information exchange in the electricity grid involves different units within different functional platforms. Currently, different SCADA (Supervisory Control and Data Acquisition) systems are used by different utilities to monitor their grid. These units often use their own information formats and databases. The information needs to be exchanged between two different systems with different information formats. In order to effectively bridge the two different information systems and protocols, the information from different systems can be converted to a common information interface format.

5.2 Information in electricity grids

Information has an influence in the management of the grid. The relevance and extent of the influence on the management depends upon the nature of the management. For instance, for the maintenance management of the grid, the maintenance and refurbishment history together with the monitoring and diagnosis information plays an important role. However, in the operational management, information of the network events, and the operation has more significance. Information of the equipment includes the design, manufacturing, operation, maintenance, refurbishment, and monitoring data [40].

Information of the equipment in the electrical grid can be grouped into following five basic categories:

- Asset data
- Operation data
- Fault data
- Maintenance data
- Monitoring and diagnostics data

A brief description of each category is presented in the following sections. The classification is presented in a generic manner so that it can be implemented for a broad class of electricity utilities.

5.2.1 Asset data

Asset data basically includes the inventory of the asset. It consists of the manufacturing data and the installation data. The design specifications, type, and other information provided by the manufacturer is a part of the asset data. Details of the installation, such as location of the asset and date of installation, can also be included in this group. Geographic information system (GIS) is also implemented to record the geographic position of the assets. Some results of the factory acceptance tests and pre-commissioning tests are also maintained in this category. The asset data are generally static.

5.2.2 Operation data

During the normal operation of the grid, a considerable amount of information is generated and stored in databases. The data includes the voltage, the load profiles, the generation data, the equipment operation configuration, etc. The operation data is used for operation of the grid. It is also useful for analysis regarding usage pattern, stress levels, etc.

Various measurement instruments are used to measure the operation data. Type of operational parameters monitored and frequency of the measurement depend upon the functionality of the equipment and its importance. The data is generally transmitted to a control center of the SCADA (Supervisory Control and Data Acquisition) system.

5.2.3 Fault data

Faults that occur in the system are also recorded and analyzed. The analysis is mainly done to identify the fault and to find the location of the fault. Current and voltage waveforms are used for the fault analysis. The fault data can be used in tracking the performance of the network as well as monitoring the stress level endured by the network components as a result of the fault. This information could be used in estimating the future performance of the network.

5.2.4 Maintenance data

Maintenance history is important for the equipment management and should be kept in a database. Maintenance activities, such as routine inspections, tests, scheduled maintenance, corrective maintenance, and repair, provide the maintenance history of the equipment. The history is useful in estimating the required future maintenance of the equipment.

5.2.5 Monitoring and diagnostics data

Various parameters such as gas in oil, partial discharge activity, or temperature are monitored in critical equipment in order to monitor the condition of the equipment. Different online monitoring systems, such as online DGA (Dissolved Gas Analysis), online PD (partial discharge), etc., have been developed which can monitor the equipment online. The volume of data generated by the online monitoring system is usually enormous as the frequency of the measurements can range from real-time to daily [40].

Various offline diagnostics tests, such as DGA analysis of oil sample in the lab or partial discharge measurement, can also be performed on the equipment. These diagnostics test can be performed routinely (e.g., yearly) or according to the need (partial discharge test after insulation failure).

5.2.6 Example: Information of a transformer

As an example, information of a transformer is presented in this section. The amount of information maintained in the utilities depends upon the size, type, rating, and importance of the transformer. Some key data of transformers listed by CIGRE working group A2.23 [40] can be summarized as follows:

- **Asset data:** Specifications, installation details, information about factory tests, pre-commissioning tests, etc.
- **Operation data:** Voltage profile, load profile, transformer configuration, etc.
- **Fault data:** Fault occurrence, types, cause, effects, outage management, and contingency analysis, etc.
- **Maintenance data:** Type of maintenance, date of maintenance, transformer oil recondition/replacement, etc.
- **Monitoring and diagnosis data:** results of DGA test, partial discharge tests, oil temperature measurements, winding hot-spot temperature estimations, etc.

5.3 Information use

The main goal of asset management is to provide reliable electrical power at an acceptable power quality to customers with an optimal economical cost and a minimal social and environmental cost. In order to fulfill this, various aspects of the grid, including the information system, should be managed in an effective way. Asset management involves multiple functional platforms [41]. The functionalities of the asset management can be categorized into three divisions based on the perspective of time [1]:

- Operational management
- Maintenance management
- Planning management

5.3.1 Operational management

The time scale of operational management ranges from real-time to short-term (up to one week ahead). The online outage management is done in real-time. Real-time protection of the system against lighting surges, switching overvoltages, and faults are performed by protection and control units. As a part of operational management, contingency analysis of the system is also performed. The operator takes appropriate actions (such as rerouting the power flow) to alleviate or to eliminate the dangerous effects of the potential problems (such as possibility of a blackout).

Operational management uses the operation data and the fault data. Most of the operation data and the fault data are obtained from the sensors in the measurement systems (MS). The data from the MS are used by the control and protection system in the substation and also sent to control centers of the SCADA system.

5.3.2 Maintenance management

Maintenance management is important for proper operation and reliability of the equipment. Depending upon the type of maintenance and the type of equipment, the time scale of the maintenance ranges from a few hours to several years. Currently most of the maintenance is time-based. Condition-based maintenance strategies are becoming more popular in the electricity grid, in which the maintenance is performed based on the condition of the equipment [2, 15]. The condition of the equipment can be estimated by various condition monitoring systems. Different rules and standards are developed for condition-based maintenance [6]. Different decision support systems (DSS) based on the rules and standards are developed [42]. These DSS can be implemented for monitoring, diagnostics, and maintenance optimization. The scheduling and management of maintenance works are done by work management systems (WMS).

Maintenance management primarily uses the monitoring and diagnostics data, the maintenance data and the asset data. The operation data and the fault data can also be used to estimate the usage of the assets and the history of faults [6].

5.3.3 Planning management

Planning management is focused on upgrading and replacing the electricity grid components. The time scale of planning management is in the range of years to decades. In the context of the liberalized market, the planning management has to balance the investment and the risks associated with it [15]. Business support systems (BSS) aid planning management of the utilities in aligning their plans according to their business goals.

Planning is also related to the operational management and the maintenance management. For instance, inadequacy of the network in the contingency analysis may lead to upgrade of the network. The history of the operational management and the maintenance management provides insight into the aging tendency of the equipment which is crucial for the downrating/uprating of the equipment and the replacement of the equipment.

5.4 Common Information Model (CIM)

In order to effectively bridge the different information systems and protocols, a common information interface is required. The information from different systems can be converted to a common information interface format by using an adapter and vice versa. By using the common information interface, a standard format of communication can be developed which can be used for cross platform communication.

The interface should be able to fulfill the requirement of different functionalities of different platforms. Furthermore, the interface should be applicable to general power utilities which have varying characteristics and requirements.

The common information model (CIM) is an abstract and formal representation of objects in the electricity grid and their attributes [43]. The CIM is developed to facilitate the information exchange between power utility companies which use different proprietary information formats [44]. The information is described by the Unified Modeling Language (UML). A brief introduction to UML is included in Appendix E. In UML, objects such as our information model are described as classes. Each class can be related to other classes in the following ways:

- **Generalization or inheritance:** is indicated by a triangle $\triangleright$ symbol. It indicates sub-classes of a parent class. Sub-classes inherit attributes of their parent class. It indicate that a sub-class is a kind of its parent class. Sub-classes inherit behaviors and attributes of its parent. In addition, the sub-class could have their own specialized behaviors or attributes.

- **Association:** is given by a line connecting classes. Association indicates that two classes are related or linked.

- **Aggregation:** is represented by a diamond $\Diamond$ symbol. Aggregation gives a “has a” relationship between the classes. Aggregation denotes that one class is contained within another class.

The CIM is maintained in the IEC standard 61970-301 [45] and the IEC standard 61968-11 [46]. The UML model of the CIM is available from the CIM user group [47]. The CIM UML Model - Version 13 Release [47] is used in this chapter, which consists of the IEC

61970 CIM version 13 release 19 and the IEC 61968 CIM version 10 release 18 UML models.

5.4.1 IEC standard 61970-301

The IEC standard 61970-301 [45] has been developed to describe the information of energy management systems. It describes an information model of components of a power system and their relationship. It consists of fourteen packages which are illustrated on Figure 5.2. The packages are described as follows (The terms used below is abbreviated package names as indicated in Figure 5.2.)[48]:

- **Core package** describes the basic objects used in this standard,
- **Wires package** includes power system network components such as lines, transformers, and switches,
- **Domain package** gives basic datatypes used for attributes of objects,
- **Topology package** defines the network configuration by connection between objects of the Core package, using the Wires package,
- **Meas package** is used for measurement of power flow and dynamic status of the topology,
- **Generation package** includes models and characteristics of generators,
- **LoadModel package** gives characteristics of load,
- **Outage package** includes information of the outages in the network, such as outage schedules and switching operations,
- **OperationalLimits package** consists of voltage, current, and power limits,
- **Protection package** contains information of protection systems,
- **Equivalents package** is used for equivalent models of the network,
- **ControlArea package** defines control of energy management system,
- **Contingency package** is used in contingency analysis of the network,
- **SCADA package** facilitates communication with SCADA system.

5.4.2 IEC standard 61968-11

The IEC standard 61968-11 [46] has been derived from the IEC standard 61790-301 and includes distribution management systems, work management systems, and customer services. Packages described in this standard are illustrated in Figure 5.3. It includes the following packages:

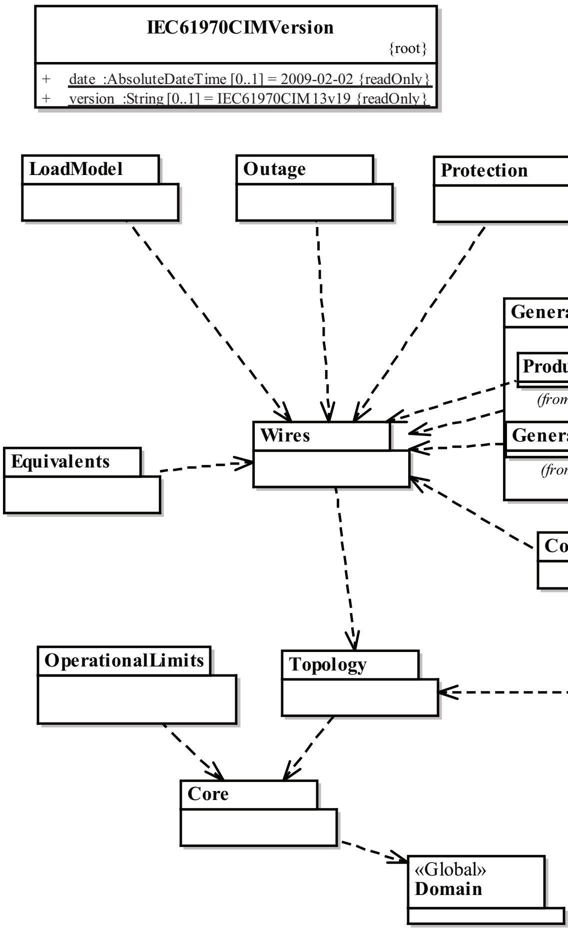

Figure 5.2: Packages included in the IEC standard 61970-301. These packages are described in the IEC 61970 CIM version 13 release 19 [47]. The dotted lines with arrows describe dependencies of packages.

- **Common package** includes common information such as time and date stamp, location information, and organization information,
- **Asset packages** include descriptions of assets and their models,
- **Work package** consists of documentation of the work management systems which includes maintenance work, installation, etc.,
- **Customers package** describes information regarding customers,
- **Metering package** is used for metering of customers.

An example of the CIM model applied on a transformer is described in the following sub-section.

5.4.3 A transformer in CIM

The information related to a transformer, such as manufacturing, installation, and operational data, is described in both the IEC standard 61790-301 and the IEC standard 61768-11. The UML model of the transformer information is shown in Figure 5.4. In this model, the transformer is implemented as a PowerTransformer class of the IEC standard 61790-301. This class is included in the Wires package since transformers are two port devices. The PowerTransformer class is a generalization of the PowerSystemResource class.

The asset data of the transformer is described as a TransformerAsset class in the IEC standard 61768-11. The TransformerAsset is a generalization of the Asset class. The PowerTransformer class from the IEC standard 61790-301 and the TransformerAsset class from the IEC standard 61768-11 are both associated through the AssetPsrRole class. In the UML, the association represents the relation between classes. Inheritance and association between the PowerTransformer class and the TransformerAsset class is illustrated in Figure 5.5.

The asset data, including the manufacturing, installation and test data, are described in the Asset class. The transformer specific asset data, such as the date of the reconditioning is described in the TransformerAsset class.

The maintenance data and the monitoring and diagnostics data are important in the maintenance management. The maintenance data is termed as the Work class in the CIM and maintained as a record for the outage management (see Figure 5.6). The monitoring and diagnostic data are also included in the TransformerObservation class and this class is linked with the TransformerAsset class via an association. The monitoring and diagnostic data are included as the attributes of the TransformerObservation class. However, no direct association is included between the Work class and the TransformerObservation class.

The monitoring and diagnostic data and the maintenance data included in the CIM, are only suitable for keeping a record of the condition and maintenance of the equipment. However, more elaborate data is required for automatic condition-based maintenance. The monitoring and diagnostic data should act as a trigger to the required maintenance actions. So the maintenance should be associated with the monitoring and diagnostic data. Therefore, more elaborate and structured data classes regarding the maintenance and the monitoring are proposed in the next section.

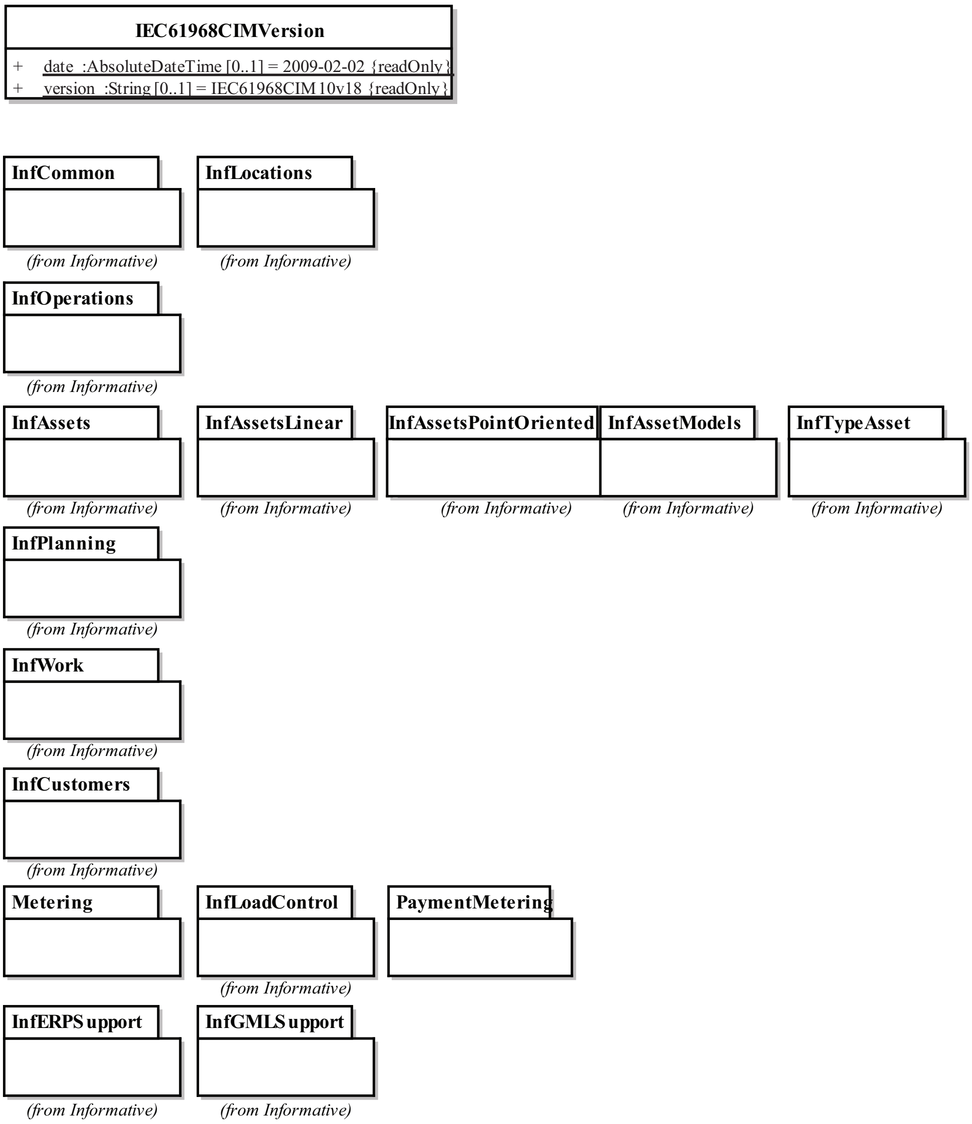

Figure 5.3: Packages included in the IEC standard 61968-11. They are described in the IEC 61968 CIM version 10 release 18 [47].

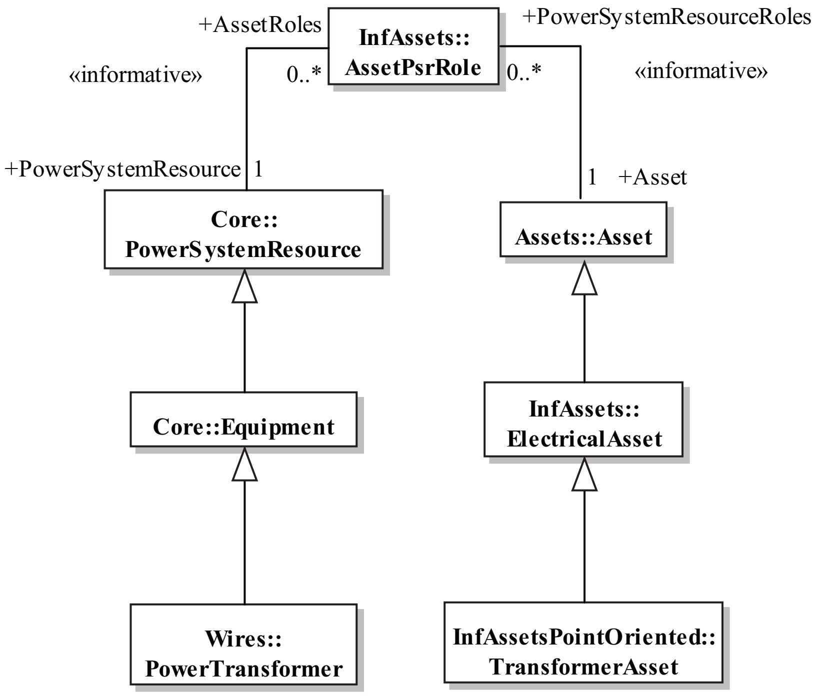

Figure 5.4: Transformer information in the CIM. The PowerTransformer class and the TransformerAsset class are associated through the AssetPsrRole class.

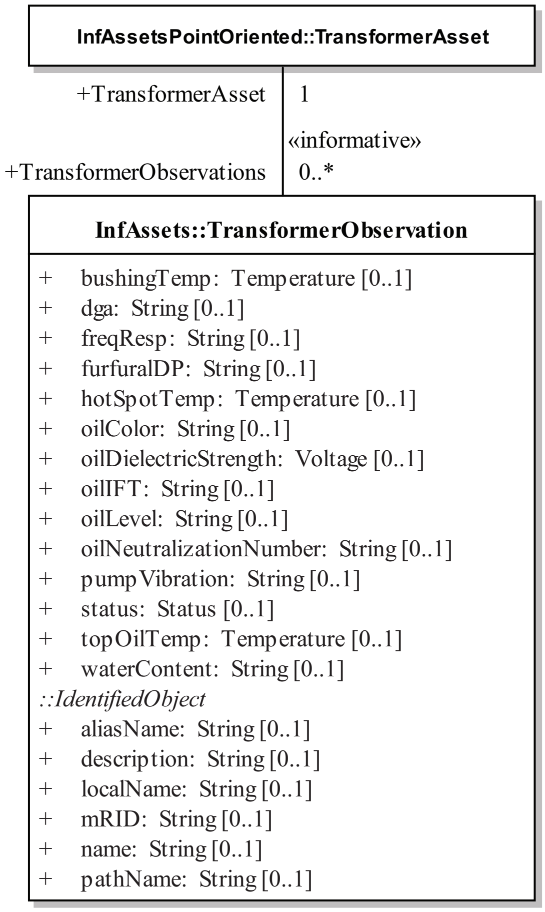

Figure 5.5: Transformer condition data in the TransformerObservation class and its link with the TransformerAsset class.

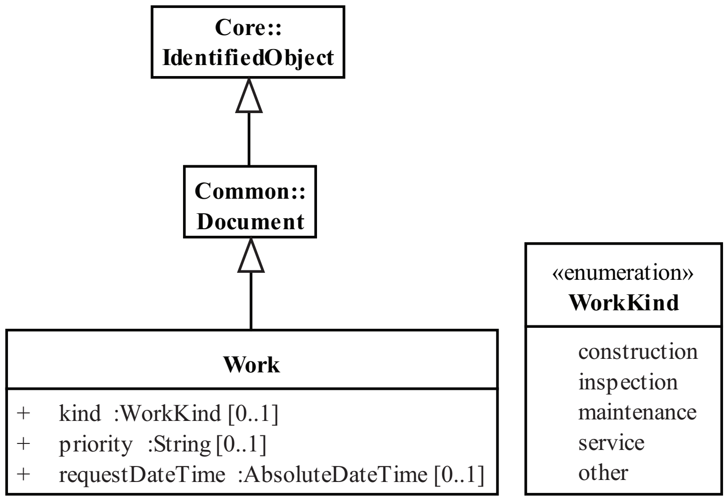

Figure 5.6: Work class in CIM. Maintenance is described as a Work class where WorkKind variable is enumerated as maintenance.

5.5 CIM extension for asset management

The CIM is extended to facilitate the maintenance activity. In the proposed CIM extension, Maintenance and Monitoring classes are proposed. As the name suggests, the Maintenance class includes information related to maintenance and the Monitoring class includes information regarding monitoring and diagnostics. The extended classes are linked to the Asset class of the IEC standard 61768-11. In order words, the Asset class contains the Maintenance class and the Monitoring class. The UML model of the proposed classes is shown in Figure 5.7.

The Asset class may consist of zero to many Maintenance classes. The Asset class also has zero to multiple monitoring and diagnostics systems represented by Monitoring classes. The Maintenance class and the Monitoring class are linked with an association since maintenance actions are based on the results of monitoring and diagnostics systems of the equipment. As indicated in Figure 5.7, multiple maintenance actions can be associated with multiple monitoring systems. The association between the maintenance and the monitoring systems is essential for the condition-based maintenance. With the assigned association, monitoring systems can trigger relevant maintenance actions based on maintenance decision support systems.

Different maintenance sub-classes for different equipment can be formulated from the Maintenance class. A specific maintenance class of the particular equipment, such as a transformer, can also be developed.

5.5.1 CIM extension for transformer

A transformer is defined as a TransformerAsset class in CIM, which is a subclass of the Asset class. For the TransformerAsset class, Maintenance and Monitoring classes specific to the transformer can be defined according to the proposed CIM extension. The Trans-

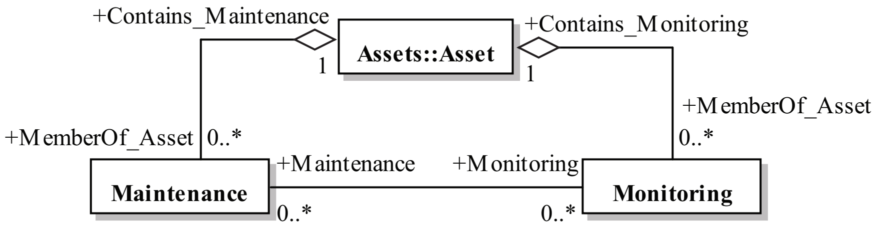

Figure 5.7: Proposed CIM extension. Maintenance and Monitoring classes are added to the Asset class of CIM. The proposed classes are linked with association.

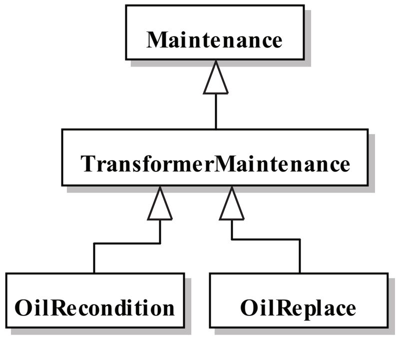

Figure 5.8: Example of different maintenance classes for transformer. The Maintenance class is taken from the proposed CIM extension (see Figure 5.7).

formerMaintenance class is defined as a generalization of the Maintenance class as shown in Figure 5.8. This class includes maintenance activities of the transformer. An example of some of the transformer maintenance activities is also presented in the figure. For example, OilRecondition and OilReplace classes represent reconditioning and replacement of transformer oil, respectively.

Similarly, the TransformerMonitoring class is a kind of Monitoring class for the transformer as shown in Figure 5.9. Different monitoring systems of the transformer, such as online DGA, offline DGA, and partial discharge measurements are represented by OnlineDGA, OfflineDGA, and PartialDischargeMeas classes, respectively. These classes are derived from the TransformerMonitoring class.

5.6 Modeling of asset management based on CIM extension

The workflow of asset management can be represented in a sequence of processes. The business processes of asset management can be modeled in terms of UML activity diagrams. Activity diagrams model the flow of processes involved in the asset management. These diagrams provide a clear insight of the processes involved. Any errors or conflicts in the process sequence can be easily identified in their activity diagrams. This is particularly important when the business processes are related to multiple departments, as it is usually

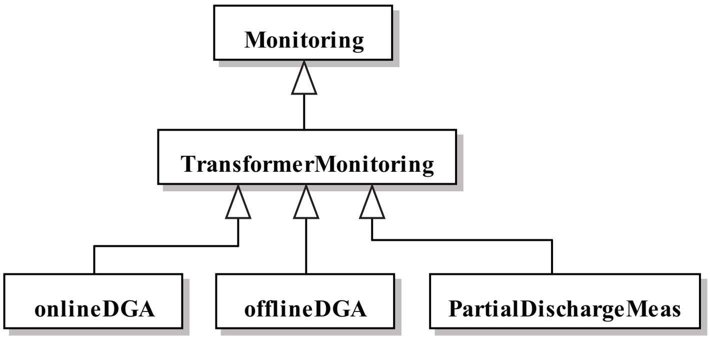

Figure 5.9: Example of different monitoring classes for transformer. Monitoring class is taken from the proposed CIM extension (see Figure 5.7).

the case with the asset management of the electricity grid.

The CIM extension can be used to facilitate the asset management of equipment as the asset management depends on information of assets. Assembly line diagrams [49] can be used to model the relation between the business process model and the information model. A modeling approach for power system maintenance is proposed in [50]. The approach uses the activity diagrams to describe the maintenance processes. The assembly line diagrams model the interaction of the processes in the activity diagrams to CIM. The interaction of processes with the CIM could be reading data from CIM, writing to data to CIM or modifying data in CIM.

The combination of activity diagrams and the assembly line diagrams results in the workflow of the process and the relation of the information model with the process. This modeling approach can be applied with the proposed CIM extension in order to model the asset management process.

5.6.1 Modeling of asset management of transformer

In order to illustrate the modeling approach, a simplified process of transformer oil maintenance is considered. In the simplified maintenance, the alarm from the online DGA monitoring system of the transformer is considered. This alarm is verified with offline DGA, in which an oil sample is tested in the lab. If the lab test confirms the alarm, the oil of the transformer is replaced. The model of the simplified process is illustrated in Figure 5.10.

The activity diagram is in the upper part of the figure. It is divided into three swim lanes which represent three departments involved in the process, namely the offline DGA lab, the maintenance management and the field crew. Activities under each department are included in their respective swim lanes.

The workflow of the process is represented as a sequence of activities in the figure. In the case of an alarm generated by the online DGA monitoring system, the alarm is followed by an offline DGA analysis which provides detailed analysis of the possible anomalies of the transformer. Depending on the analysis result, appropriate maintenance decisions should be taken, such as schedule another DGA analysis in the near future, oil reconditioning, oil replacement, etc. In this example, only the oil replacement is taken into account.

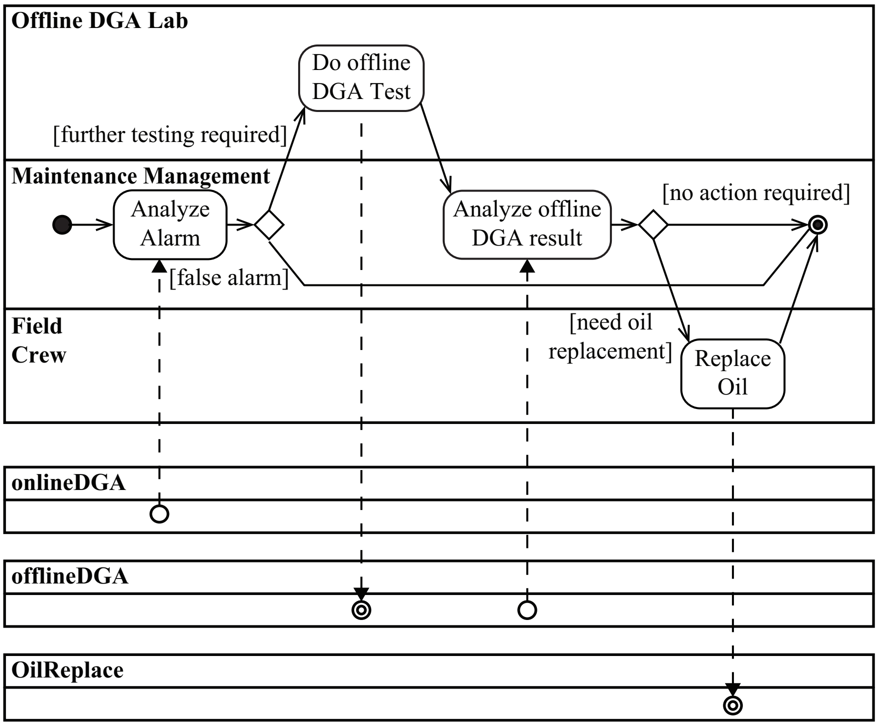

Figure 5.10: Proposed modeling of process of transformer oil maintenance. The activity diagram of process flow is given in the upper part. The processes are linked with the extended CIM classes. Three swim lanes in the activity diagram represent the three departments involved in the process.

The Monitoring and Maintenance classes involved in the process are in the lower part of the figure. These classes are taken from the extended CIM. The actions performed by the activities on the extended CIM classes are represented by assembly line diagram (represented by dotted lines in the figure). For instance, the activity of an offline DGA test writes the test results in the OfflineDGA class. The results are read by the activity of analyzing the test result. The information exchange between the offline DGA lab and the maintenance management is achieved through the extended CIM.

5.7 CIM extension for dynamic loading of transformers in a network

Distributed control of dynamic loading of transformers in a network was presented in Chapter 4 in Section 4.6. In that section, dynamic loading of transformers was achieved by using Transformer Loading agents and an Optimal Power Flow agent. The interaction between these agents was illustrated in Figure 4.7.

The transformer loading agent receives the maximum hot-spot temperature from the Loading Regime Selector agent. It also receives the predicted loading of the Transformer from the Optimal Power Flow agent. Based on these inputs, the agent then calculates the dynamic loading limit for the transformer. The Optimal Power Flow agent has multiple Transformer loading agents which are responsible for multiple transformers in the network. The Optimal Power Flow agent takes dynamic loading limits of all the transformers in the network and controls the network such that for each transformer its loading is below its dynamic loading limit. The Optimal Power Flow agent also estimates the predicted loading of the transformers and sends them to the corresponding Transformer Loading agents.

The proposed dynamic loading of the transformers can be implemented using a CIM extension. The transformer loading is monitored in the dynamic loading. Thus TransformerLoad class is added as a child of TransformerMonitoring class. The top oil temperature is calculated from transformer loading in Section 4.6. In order to demonstrate the capability of adding monitoring in the proposed framework, we consider the top-oil temperature to be monitored, in this section. The top-oil temperature measurement will be obtained from a sensor and hot-spot temperature is predicted based on the top oil temperature and the transformer loading. Thus, TopOilTemp class is also added to TransformerMonitoring class. The predicted loading, estimated by the Optimal Power Flow agent, is also added as PredictedLoading class. The class diagram of the added CIM extensions is illustrated in Figure 5.11.

The dynamic loading for the transformers also includes two types of setpoints, namely the maximum hot-spot temperature limit and the dynamic loading limit. These limits are basically regulating parameters as these limits regulate corresponding states. In the CIM, such regulations are modeled as regulating control classes. The regulation class is normally used to represent voltage or flow regulation in the power grid. Two new classes, MaxHotSpotTemp and TransformerLoadingLimit classes, are added to the CIM as shown in Figure 5.12. These classes are a generalization of RegulatingControl class so they derive targetValue attribute for RegulatingControl class. So, MaxHotSpotTemp.targetValue would include the maximum setpoint for the Transformer Loading agent and TransformerLoadingLimit.targetValue would include the dynamic loading limit for the Optimal Power Flow

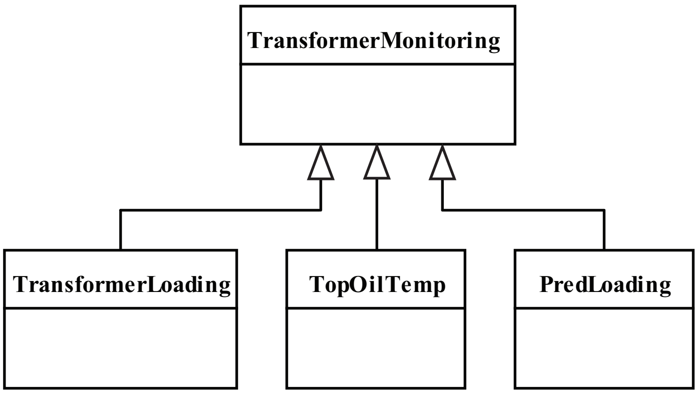

Figure 5.11: The CIM extension of TransformerMonitoring class for including the dynamic loading of transformer. TransformerLoad class and TopOilTemp class represent the transformer load monitoring and the top-oil temperature monitoring. PredictedLoading class represents the predicted loading estimated by the optimal power flow agent.

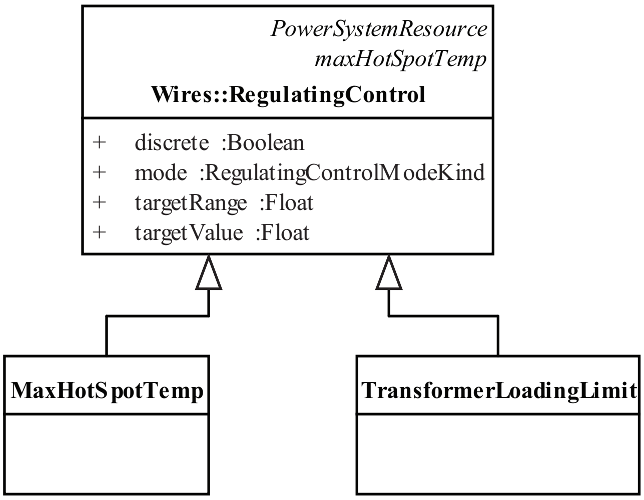

Figure 5.12: Classes for the maximum hot-spot temperature and the dynamic loading limit. These classes are generalized from the existing CIM class, Regulating control. This class is used for regulation of certain state of the network thus this class is useful to define setpoints of hot-spot temperature and loading.

agent.

These CIM extensions can be used in storing the information required for the dynamic loading of transformer in a network.

5.7.1 Modeling of dynamic loading of transformers in a network

The process of the dynamic loading of transformers in a network can be modeled using an activity diagram. The interactions of the process and the proposed CIM extension can be visualized with an assembly line diagram. The activity diagram and the assembly line diagram is shown in Figure 5.13. As shown in the first swim lane of the figure, the transformer loading agent gets the maximum hot-spot temperature and the top oil temperature from maxHotSpotTemp and topOilTemp classes, respectively. Then the agent retrieves the predicted loading for the prediction horizon from predictedLoading class. The calculated dynamic loading limit for the prediction horizon is stored in loadingLimit class. The optimal power flow agent picks up this dynamic loading limit from loadingLimit class. The agent also retrieves the loading of its transformer from transformerLoading class. The optimal power flow agents then controls the network according to the dynamic loading limit. This control is continued for the defined prediction horizon. At the end of this period, the optimal power flow agent calculates the predicted transformer loading and writes it in predictedLoading class.

Figure 5.13 shows the information flow from two agents, the Transformer agent and the Optimal Power Flow agent. The dynamic loading limit of the transformer is transferred from the Transformer Loading agent to the Optimal Power Flow agent through transformerLoading class. Similarly, the predicted loading of the transformer is transferred from Optimal Power Flow agent to the Transformer Loading agent through predictedLoading class.

5.8 Conclusions

In this chapter, a common information interface has been proposed for the electricity grid. The interface facilitates information exchange between systems with different information formats. The information of different systems can be converted into a common information format. An international standard, the CIM, was chosen as the common information format. The CIM is extended to incorporate the condition-based maintenance philosophy. Maintenance information and monitoring and diagnostics information are included in the extended CIM. The maintenance and monitoring data are coupled by defining an association between them. The link between the maintenance and the condition is essential for the condition-based maintenance, which is included in the extended information model.

A modeling approach for the asset management is presented and the use of the CIM extension is illustrated using this approach. The CIM extension facilitates information exchange between different departments.

The CIM is also extended to include new classes required for the dynamic loading of transformer in a network. With the extended CIM, communication between the Transformer agent and the Optimal Power Flow agent can be achieved. The process involved in the dynamic loading of transformers in a network can also be modeled using the CIM extension. Thus this extension is also suitable for the intelligent network approach proposed in Chapter 4.

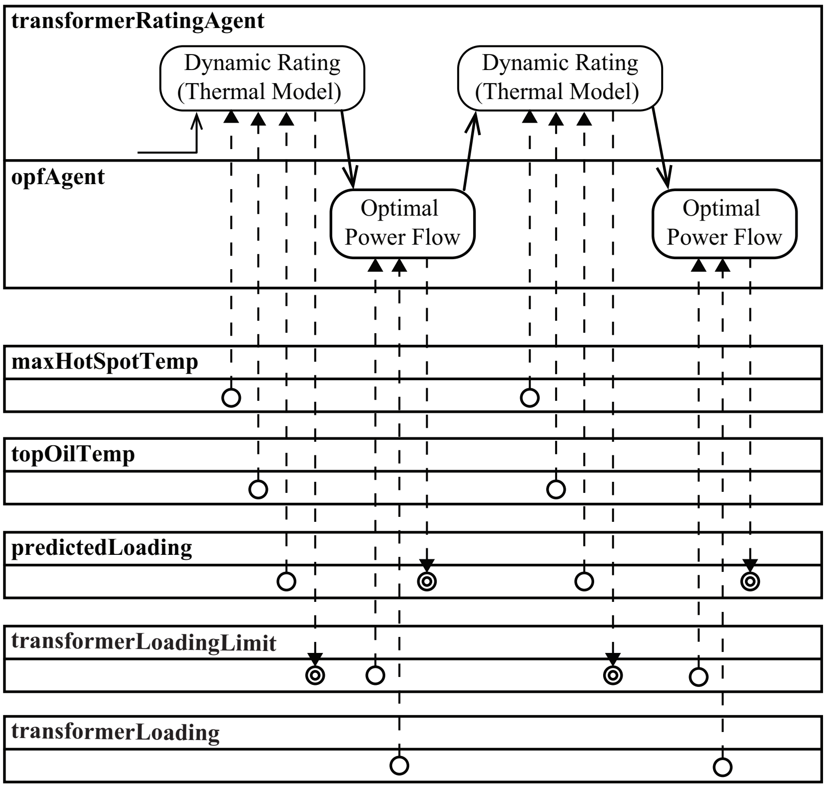

Figure 5.13: Modeling of process of dynamic loading of transformers in a network. The activity diagram (upper part of the figure) includes processes of Transformer Loading Agent and Optimal Power Flow Agent. Their interaction with CIM (lower part of the figure) are illustrated by assembly line diagram (represented by dotted lines in the figure).

Chapter 6

Conclusions and future research

6.1 Conclusions

In this thesis, a basis for intelligent grid concept was investigated. Recent developments in intelligent control were studied and presented. Concept of agents and model predictive control was presented. These two concepts in the field of intelligent systems are combined to form a basis for the intelligent framework to control the grid.

In this framework, a predictive health model for equipment in the electric grid has been developed. This model laid the groundwork for developing the framework of the predictive health management. This framework uses the predictive health model in order to optimize the usage and the maintenance actions of equipment. The concept of an intelligent component has been developed, which utilizes this framework to provide a local optimal solution for managing assets.

The optimal local solutions of each component within a network have to be combined and coordinated, in order to achieve an optimal global solution. In order to do this, an effective communication language is needed to share information between these intelligent components. The Common Information Model (CIM) has been used as a basis for the information model and an extension of the CIM has been developed. This extension suits the requirements of the predictive health management and enables information exchange between all intelligent components in the network, regardless of equipment type.

An intelligent network framework has been developed in this thesis. Within this intelligent network framework, intelligent agents communicate and coordinate with each other, in order to solve a global optimization problem by a collaborative effort and solving local optimization problems.

With this thesis, we have demonstrated that the operational, maintenance, and planning management of the grid are not mutually exclusive entities. Decisions made on one level of management have repercussions on other levels of management. In order to achieve an optimal utilization of equipment in the grid, the operational, maintenance, and planning managements have to be coordinated.

These management levels have different time frames and their own diverse objectives. We have shown that combining these management levels in one big global problem is not practical. As soon as the size of the network in consideration approaches the order of the magnitude of existing grids, its global problem would quickly become insurmountable.

To solve this problem, a distributed approach was proposed. In that regard, the concept of intelligent components was introduced. The agent concept has been embedded within the intelligent components, which has been used to divide a global problem into modular and comprehensible local problems.

A framework for the optimization of the health state of equipment has been defined in this thesis. This framework is based on the model predictive control concept, thus the tools and techniques that are already available for the model predictive control concept are also applicable to this framework. It also uses a model based on the equipment health state, the predictive health model. This predictive health model provides an opportunity to model the evolution of the health state of electrical equipment, based on usage and maintenance history. By involving the health state into a model, it is possible to use equipment up to its optimal limit, without accelerating the deterioration of its health state.

In addition, the intelligent component concept is modular in nature, can therefore be adapted to incorporate future changes in the model. The intelligent component can also be easily updated to any new modeling concept, as illustrated by adding the simplified method of transformer loading in which no load prediction is provided.

The optimization process also has been incorporated in the framework. This process uses the predictive health model to generate an optimal solution. The validity of this solution will depend upon the accuracy of the model. Since the whole system is modular, upgrade or modification of equipment means that only the health model needs to be adapted. The optimization would still work.

This predictive health model would give predictions of its health state. By using this prediction, the solution would be optimal for the considered prediction horizon, which could be changed according to the level of management involved. The operational management, for instance, uses a shorter time horizon compared to the planning management.

With the diversity of the systems and equipment involved in the grid, a common information exchange is required for a seamless communication between intelligent agents. This could be delivered by the Common Information Model (CIM). The CIM is designed to handle operational and planning management of the grid thus the maintenance management aspect is scarcely incorporated in the CIM. By using the flexibility of the CIM, an extension has been developed for this purpose. The developed extension can be used in the intelligent network for bridging the information gap.

A scheme has been developed to address the time frame differences in the operational, maintenance, and planning management. With in the intelligent network, intelligent components belonging to the operational management could have a shorter time horizon and intelligent components of the maintenance management could operate in a longer time horizon.

The implementation of the proposed framework is also presented. As a part of intelligent component, the dynamic loading control scheme was developed in the transformer loading. It is demonstrated that using this framework, the dynamic loading of transformer can be achieved while considering the health state of the transformer.

As a part of implementation of intelligent network, the optimal power flow agent is added to the transformer loading agent. Using the concept of intelligent networks, these two agents were able to coordinate between each other in order to optimally control the loading of the transformer. The flexibility of the intelligent network concept was also demonstrated by considering different kinds of transformer agents. The use of the CIM extension designed in this thesis was also illustrated. Use of the CIM extension in the information exchange between the transformer agent and the optimal power flow agent was illustrated.

6.1.1 Applicability of the framework in the control of the future power grid

The drivers of the future power grid were presented in this thesis. The deregulation of the electricity market has changed the financial aspect of the power grid. For every investment in the grid, there is a need for financial justification. The aging of the grid is a major issue with most of the grid components which are nearing the end of their operational lifetime in near future. These two factors lead towards a need for optimal utilization of the grid. Moreover, the share of renewable energy sources is increasing rapidly. The grid is not operating according to the conventional philosophy with which it was designed for. There is a need for redesigning the overall grid management philosophy.

There have been a flux of technological development in the field of communication and computational power. These developments could be incorporated in the grid for better utilization, management, and control of the grid. We have also gained considerably better understanding of operation of the grid. New monitoring systems have been developed that can provide better observability of the situation of the grid. With various researches and new concepts developed for the grid, we have a better understanding of the operation, maintenance, and planning of the grid. Therefore there have been significant strides in the field of autonomous and intelligent control. These control techniques could be implemented in the grid.

We already have a significant investment in the grid infrastructure. There have been an enormous engineering effort in the grid redesign and implementation. The electrical grid is a complex system with multiple facets which need to be considered. This certainly does not limit us from improving the grid. We need to adapt our future improvement in the grid such that it retains positive aspects of our grid as well as improves it.

In order to achieve this goal, the grid control system should be flexible enough that it can incorporate various aspects. We propose a framework of the control of the future grid which is applicable for various new developments and at the same time is also incorporating the existing essential control system. The framework presented in this thesis complements this need. The major highlights of the framework with regard to these aspects are as follows:

- The framework utilizes the current development in the intelligent control algorithms.
- It provides distributed design which enables co-existence of different control philosophies.
- The framework is flexible. A module of the framework (intelligent component) could easily be redesigned/replace according to the need.
- The framework provides an opportunity to optimize the utilization of the grid component.
- The framework is not specific to any particular aspects of the grid thus can be implemented in multiple control principles.

6.2 Future research

This thesis laid out the groundwork for intelligent components and intelligent networks. Further research is required to broaden this foundation, in order to implement the work presented in this thesis. Possibilities for further research are listed as follows:

6.2.1 Predictive health models

The predictive health model of the thermal dynamics of transformers has been introduced in this thesis in the form of a case study. In order to apply the concept of the intelligent network, the predictive health model should be extended to cover other aspects of transformers, such as the model of the paper degradation of transformers in the predictive health model framework. Models of other equipment, such as cables, circuit breakers, generators, etc. should also be developed. Finally, an extensive library of predictive health models for different components of the grid, as well as different aspects of the health state should be accumulated. This library could be used for broadening the application of the concept of intelligent network.

There has been some significant monitoring system integrations in new cables such as the integration of distributed temperature sensors in some cables [51]. These monitoring systems could be utilized for the dynamic rating of these cables. Therefore such cables could be one of the most attractive candidates for the immediate development and the possible implementation of the predictive health model.

6.2.2 CIM extensions

In this thesis, the CIM extension for information of transformers has been considered. Other equipment should also be incorporated in the CIM extension. The CIM version used (version 13) was the current version at the time of the research. Currently, a newer version of the CIM (version 16) is already available. This newer version should be incorporated in the framework.

CIM provides an ontology for the agent system. Ontology is a common language or vocabulary used by agents. With this ontology, various standard agent communication languages, such as Foundation for Intelligent Physical Agents - Agent Communication Language (FIPA-ACL) Standards [52], can be utilized. With this, various software development tools/framework, such as JADE (Jave Agent DEvelopment Framework) [53], could be utilized for implementing the agent system.

6.2.3 Implementations

The research performed and presented in of this thesis would be instrumental for the optimal utilization of the grid. In order to take advantage of this fact, the concept developed in the grid should be implemented in the electrical grid. In the beginning of the implementation phase, a pilot project should be initiated which implements the concept in certain components of the grid, such as transformers. A good start would be the case study mentioned in this thesis, namely the dynamic loading of the transformer using its thermal model. The implementation could be expanded to cover other aspects of the transformer, such as the insulation paper degradation. Furthermore, other equipment in the grid, such as cables, circuit breakers, etc. should also be implemented.

The deployment of the concept presented in this thesis could be used in various phases. In the initial phase, a proof of concept could be realized. Even though the framework is capable of the total control of the system, this can be initially introduced as a monitoring system. For instance, the dynamic loading limits generated by this framework could be initially utilized as information only in the current system. As we have experience with this system and as we gain more insight and more confidence in this system, it could be deployed in the full phase.

Another potential implementation is in new network developments. The framework does not require an extensive cost for implementation as most of it is a control algorithm, except for additional costs of monitoring. These systems can be deployed together with new developments, such as new equipment/network installation.

The distribution system is undergoing major changes in terms for automation. Traditionally, distribution system lack extensive automation. New developments, such as smart metering, grid monitoring, automatic controls, etc,. are being introduced in the distribution. This gives us an opportunity to bundle this framework along with the new design. This would result in a small incremental cost but has a potential to provide a greater benefit in the long run.

Appendix A

Gradients of the cost function and its constraints

In Chapter 3, gradients of the cost function and constraints of the optimization problem are used for solving the optimization problem. Using these gradients reduces the number of iteration of the solution, thus reducing the execution time. The optimization problem used in 3.18 of Chapter 3 is as follows:

$$\min_{\alpha, u_{\mathrm{I,max}}(k),\ldots,u_{\mathrm{I,max}}(k+N-1)} \sum_{l=0}^{N-1} \left[c_1 \left(u_{\mathrm{I,max}}(k+l) - \alpha u_{\mathrm{I,pred}}(k+l) \right)^2 \right] - c_2 \alpha, \tag{A.1}$$

subject to

$$\begin{aligned} x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), u_{\mathrm{I,max}}(k+l)), \\ x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), u_{\mathrm{I,max}}(k+l)), \\ x_{\theta,\mathrm{hs}}(k+l+1) &\leq x_{\theta,\mathrm{hs,max}}, \\ \alpha &\geq 1, \\ &\text{for } l = 0, \ldots, N-1. \end{aligned}$$

A.1 Gradient of the cost function

The cost function in (A.1) can be defined as:

$$\begin{aligned} &J_{\mathrm{total}}\left(u_{\mathrm{I,max}}(k), \ldots, u_{\mathrm{I,max}}(k+N-1), \alpha\right) = \\ &\sum_{l=0}^{N-1} \left[c_1 \left(u_{\mathrm{I,max}}(k+l) - \alpha u_{\mathrm{I,pred}}(k+l) \right)^2 \right] - c_2 \alpha. \end{aligned} \tag{A.2}$$

The gradient (partial derivative) of the cost function with respect to $u_{\mathrm{I,max}}(k+l)$ can be calculated as follows:

$$\begin{aligned} &\frac{\partial J_{\mathrm{total}}}{\partial u_{\mathrm{I,max}}(k+l)} = 2c_1 \left(u_{\mathrm{I,max}}(k+l) - \alpha u_{\mathrm{I,pred}}(k+l) \right), \\ &\text{for } l = 0, \ldots, N-1. \end{aligned} \tag{A.3}$$

The gradient (partial derivative) of the cost function with respect to α can be calculated as follows:

$$\frac{\partial J_{\text{total}}}{\partial \alpha} = \sum_{l=0}^{N-1} \left[-2c_1 u_{\text{I,pred}}(k+l)\left(u_{\text{I,max}}(k+l) - \alpha u_{\text{I,pred}}(k+l)\right)\right] - c_2, \tag{A.4}$$
$$\text{for } l = 0,\ldots,N-1.$$

A.2 Gradient of the constraint of the top-oil model

The first constraint in the optimization problem(A.1) is derived from the top-oil model of the transformer. The constraint derived from the top-oil model is:

$$\begin{aligned}
&x_{\theta,\text{oil}}(k+l+1) = f_{\text{oil}}(x_{\theta,\text{oil}}(k+l), u_{\theta,\text{amb}}(k+l), u_{\text{I,max}}(k+l)),\\
&x_{\theta,\text{oil}}(k+l+1) - f_{\text{oil}}(x_{\theta,\text{oil}}(k+l), u_{\theta,\text{amb}}(k+l), u_{\text{I,max}}(k+l)) = 0,\\
&\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{A.5}$$

The function f_{oil} of the top-oil model is given in (3.14) as:

$$\begin{aligned}
f_{\text{oil}} =& x_{\theta,\text{oil}}(k+l) + \frac{h}{\mu_{\text{pu}}(k+l)^n \tau_{\text{oil,rated}}} \left[\frac{1+Ru_{\text{I,max}}(k+l)^2}{1+R} \mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{oil,rated}} \right.\\
&\left. - \frac{(x_{\theta,\text{oil}}(k+l) - u_{\theta,\text{amb}}(k+l))^{n+1}}{\Delta\theta^n_{\text{oil,rated}}}\right],\\
&\text{for } l = 0,\ldots,N-1,
\end{aligned} \tag{A.6}$$

where from (3.13)

$$\mu_{\text{pu}}(k+l) = \frac{\exp\left(\dfrac{2797.3}{x_{\theta,\text{oil}}(k+l)+273}\right)}{\exp\left(\dfrac{2797.3}{\theta_{\text{oil,rated}}+273}\right)}, \tag{A.7}$$
$$\text{for } l = 0,\ldots,N-1.$$

The constraint given in (A.5) can be redefined as:

$$\begin{aligned}
&F_{\text{oil}}\left(x_{\theta,\text{oil}}(k+l+1), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)\right) =\\
&\mu_{\text{pu}}(k+l)^n \tau_{\text{oil,rated}}\left(x_{\theta,\text{oil}}(k+l+1) - x_{\theta,\text{oil}}(k+l)\right)\\
&-h\left[\frac{1+Ru_{\text{I,max}}(k+l)^2}{1+R}\mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{oil,rated}}\right.\\
&\left. - \frac{(x_{\theta,\text{oil}}(k+l) - u_{\theta,\text{amb}}(k+l))^{n+1}}{\Delta\theta^n_{\text{oil,rated}}}\right] = 0,\\
&\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{A.8}$$

The gradient of the top-oil model constraint with respect to $x_{\theta,\text{oil}}(k+l+1)$ is given by:

$$\begin{aligned} &\frac{\partial F_{\text{oil}}}{\partial x_{\theta,\text{oil}}(k+l+1)} = \mu_{\text{pu}}(k+l)^n \tau_{\text{oil,rated}}, \\ &\text{for } l = 0,\ldots,N-1. \end{aligned} \tag{A.9}$$

The gradient of the top-oil model constraint with respect to $x_{\theta,\text{oil}}(k+l)$ is given by:

$$\begin{aligned} &\frac{\partial F_{\text{oil}}}{\partial x_{\theta,\text{oil}}(k+l)} = \\ &\frac{\partial \mu_{\text{pu}}(k+l)^n}{\partial x_{\theta,\text{oil}}(k+l)} \tau_{\text{oil,rated}} \left(x_{\theta,\text{oil}}(k+l+1) - x_{\theta,\text{oil}}(k+l)\right) \\ &+ \mu_{\text{pu}}(k+l)^n \tau_{\text{oil,rated}} \\ &-h \left[\frac{1+Ru_{\text{I,max}}(k+l)^2}{1+R} \frac{\partial \mu_{\text{pu}}(k+l)}{\partial x_{\theta,\text{oil}}(k+l)^n} \Delta\theta_{\text{oil,rated}} \right. \\ &\left. - (n+1) \frac{(x_{\theta,\text{oil}}(k+l) - u_{\theta,\text{amb}}(k+l))^n}{\Delta\theta^n_{\text{oil,rated}}} \right], \\ &\text{for } l = 0,\ldots,N-1, \end{aligned} \tag{A.10}$$

where from (A.7)

$$\begin{aligned} &\frac{\partial \mu_{\text{pu}}(k+l)^n}{\partial x_{\theta,\text{oil}}(k+l)} = -n\mu_{\text{pu}}(k+l)^n \left(\frac{2797.3}{(x_{\theta,\text{oil}}(k+l)+273)^2} \right), \\ &\text{for } l = 0,\ldots,N-1. \end{aligned} \tag{A.11}$$

The gradient of the top-oil model constraint with respect to $u_{\text{I,max}}(k+l)$ is given by:

$$\begin{aligned} &\frac{\partial F_{\text{oil}}}{\partial u_{\text{I,max}}(k+l)} = -h \frac{2Ru_{\text{I,max}}(k+l)}{1+R} \mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{oil,rated}}, \\ &\text{for } l = 0,\ldots,N-1. \end{aligned} \tag{A.12}$$

A.3 Gradient of the constraint of the hot-spot model

The second constraint in the optimization problem (A.1) is derived from the hot-spot model of the transformer. The constraint derived from the hot-spot model is:

$$\begin{aligned} &x_{\theta,\text{hs}}(k+l+1) = f_{\text{hs}}(x_{\theta,\text{hs}}(k+l), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)), \\ &x_{\theta,\text{hs}}(k+l+1) - f_{\text{hs}}(x_{\theta,\text{hs}}(k+l), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)) = 0, \\ &\text{for } l = 0,\ldots,N-1. \end{aligned} \tag{A.13}$$

The function f_{hs} of the hot-spot model is given in (3.17) as:

$$
\begin{aligned}
f_{\text{hs}} =& x_{\theta,\text{hs}}(k+1) \\
&+ \frac{h}{\mu_{\text{pu}}(k+l)^n \tau_{\text{wdg,rated}}} \Big[u_{\text{I,max}}(k+1)^2 P_{\text{cu,pu}}(k+l) \mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{hs,rated}} \\
&- \frac{(x_{\theta,\text{hs}}(k+l) - x_{\theta,\text{oil}}(k+l))^{n+1}}{\Delta\theta^n_{\text{hs,rated}}} \Big], \\
&\text{for } l = 0, \ldots, N-1,
\end{aligned}
\tag{A.14}
$$

where from (3.16)

$$
\begin{aligned}
&P_{\text{cu,pu}}(k+l) = P_{\text{cu,dc,pu}} \frac{235 + x_{\theta,\text{hs}}(k+l)}{235 + \theta_{\text{hs,rated}}} + P_{\text{cu,eddy,pu}} \frac{235 + \theta_{\text{hs,rated}}}{235 + x_{\theta,\text{hs}}(k+l)}, \\
&\text{for } l = 0, \ldots, N-1.
\end{aligned}
\tag{A.15}
$$

The constraint given in (A.13) can be redefined as:

$$
\begin{aligned}
&F_{\text{hs}}\left(x_{\theta,\text{hs}}(k+l+1), x_{\theta,\text{hs}}(k+l), x_{\theta,\text{oil}}(k+l), u_{\text{I,max}}(k+l)\right) = \\
&\mu_{\text{pu}}(k+l)^n \tau_{\text{wdg,rated}} \left(x_{\theta,\text{hs}}(k+l+1) - x_{\theta,\text{hs}}(k+l)\right) \\
&-h \Big[u_{\text{I,max}}(k+l)^2 P_{\text{cu,pu}}(k+l) \mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{hs,rated}} \\
&- \frac{(x_{\theta,\text{hs}}(k+l) - x_{\theta,\text{oil}}(k+l))^{n+1}}{\Delta\theta^n_{\text{hs,rated}}} \Big], \\
&\text{for } l = 0, \ldots, N-1.
\end{aligned}
\tag{A.16}
$$

The gradient of the hot-spot model constraint with respect to $x_{\theta,\text{hs}}(k+l+1)$ is given by:

$$
\begin{aligned}
&\frac{\partial F_{\text{hs}}}{\partial x_{\theta,\text{hs}}(k+l+1)} = \mu_{\text{pu}}(k+l)^n \tau_{\text{wdg,rated}}, \\
&\text{for } l = 0, \ldots, N-1.
\end{aligned}
\tag{A.17}
$$

The gradient of the hot-spot model constraint with respect to $x_{\theta,\text{hs}}(k+l)$ is given by:

$$
\begin{aligned}
&\frac{\partial F_{\text{hs}}}{\partial x_{\theta,\text{hs}}(k+l)} = -\mu_{\text{pu}}(k+l)^n \tau_{\text{wdg,rated}}, \\
&-h \left[u_{\text{I,max}}(k+l)^2 \frac{\partial P_{\text{cu,pu}}(k+l)}{\partial x_{\theta,\text{hs}}(k+l)} \mu_{\text{pu}}(k+l)^n \Delta\theta_{\text{hs,rated}} \right. \\
&\left. - (n+1) \frac{(x_{\theta,\text{hs}}(k+l) - x_{\theta,\text{oil}}(k+l))^n}{\Delta\theta^n_{\text{hs,rated}}} \right], \\
&\text{for } l = 0, \ldots, N-1,
\end{aligned}
\tag{A.18}
$$

where from (A.15)

$$
\begin{aligned}
&\frac{\partial P_{\text{cu,pu}}(k+l)}{\partial x_{\theta,\text{hs}}(k+l)} = P_{\text{cu,dc,pu}} \frac{1}{235 + \theta_{\text{hs,rated}}} - P_{\text{cu,eddy,pu}} \frac{235 + \theta_{\text{hs,rated}}}{(235 + x_{\theta,\text{hs}}(k+l))^2}, \\
&\text{for } l = 0, \ldots, N-1.
\end{aligned}
\tag{A.19}
$$

The gradient of the hot-spot model constraint with respect to $x_{\theta,\mathrm{oil}}(k+l)$ is given by:

$$\begin{aligned}
&\frac{\partial F_{\mathrm{oil}}}{\partial x_{\theta,\mathrm{oil}}(k+l)} = \\
&-h\left[u_{\mathrm{I,max}}(k+l)^2 P_{\mathrm{cu,pu}}(k+l)\frac{\partial \mu_{\mathrm{pu}}(k+l)^n}{x_{\theta,\mathrm{oil}}(k+l)}\Delta\theta_{\mathrm{hs,rated}}\right. \\
&\left.+\,(n+1)\frac{(x_{\theta,\mathrm{hs}}(k+l)-x_{\theta,\mathrm{oil}}(k+l))^n}{\Delta\theta_{\mathrm{hs,rated}}^n}\right], \\
&\text{for } l=0,\ldots,N-1.
\end{aligned} \tag{A.20}$$

The gradient of the hot-spot model constraint with respect to $u_{\mathrm{I,max}}(k+l)$ is given by:

$$\frac{\partial F_{\mathrm{oil}}}{\partial u_{\mathrm{I,max}}(k+l)} = -h\left[2u_{\mathrm{I,max}}(k+l)P_{\mathrm{cu,pu}}(k+l)\mu_{\mathrm{pu}}(k+l)^n\Delta\theta_{\mathrm{hs,rated}}\right] \tag{A.21}$$

for $l=0,\ldots,N-1$.

Appendix B

Algorithm for dynamic loading in absence of predicted loading

In Section 3.8.2 of this thesis, an algorithm is proposed for solving the case of dynamic loading in absence of predicted loading. The optimization problem is simplified in this case and reduced to a set of non-linear equations. These equations given in (3.21) are as follows:

$$\begin{aligned}
x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), u_{\mathrm{I,max}}(k+l)),\\
u_{\mathrm{I,max}}(k+l+1) &= u_{\mathrm{I,max}}(k+l),\\
x_{\theta,\mathrm{hs}}(k+N-1) &= x_{\theta,\mathrm{hs,max}},\\
&\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{B.1}$$

This set of non-linear equations can be solved by a non-linear equation solver algorithm which involves an iterative method. A solution based on the bisection method is presented in this appendix.

In (B.1), $u_{\mathrm{I,max}}(k+l+1) = u_{\mathrm{I,max}}(k+l)$ for the entire prediction horizon (for $l = 0,\ldots,N-1$), which means that the maximum transformer loading $u_{\mathrm{I,max}}$ is constant for the entire prediction horizon, given by:

$$\begin{aligned}
u_{\mathrm{I,max}}(k+l+1) = u_{\mathrm{I,max}}(k+l) = \mathrm{u}_{\mathrm{I,max}}(k),\\
\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{B.2}$$

Then (B.1) would be:

$$\begin{aligned}
x_{\theta,\mathrm{oil}}(k+l+1) &= f_{\mathrm{oil}}(x_{\theta,\mathrm{oil}}(k+l), u_{\theta,\mathrm{amb}}(k+l), \mathrm{u}_{\mathrm{I,max}}(k)),\\
x_{\theta,\mathrm{hs}}(k+l+1) &= f_{\mathrm{hs}}(x_{\theta,\mathrm{hs}}(k+l), x_{\theta,\mathrm{oil}}(k+l), \mathrm{u}_{\mathrm{I,max}}(k)),\\
x_{\theta,\mathrm{hs}}(k+N-1) &= x_{\theta,\mathrm{hs,max}},\\
&\text{for } l = 0,\ldots,N-1.
\end{aligned} \tag{B.3}$$

At the end of the prediction horizon $l = N-1$, the hot-spot temperature $x_{\theta,\text{hs}}(k+N-1)$ would reach the maximum limit $x_{\theta,\text{hs,max}}$. In essence, we are determining the constant transformer loading limit which would cause the hot-spot temperature to reach its maximum limit at the end of the prediction horizon. If the actual loading does not exceed this maximum limit then the hot-spot temperature will not exceed its limit.

The algorithm used for the transformer loading is shown in Figure B.1. In this algorithm, an initial guess of the maximum loading $u_{\text{I,max,init}}$ is considered. The hot-spot temperature at the end of the prediction horizon $x_{\theta,\text{hs}}(k+N-1)$ is calculated and it is checked if this temperature is nearly equal to the maximum hot-spot temperature $x_{\theta,\text{hs,max}}$ by a tolerance value ε. If this criterion is not met then the loading is incremented or decremented by a value given by Δu. This value is corrected according to the bisection algorithm.

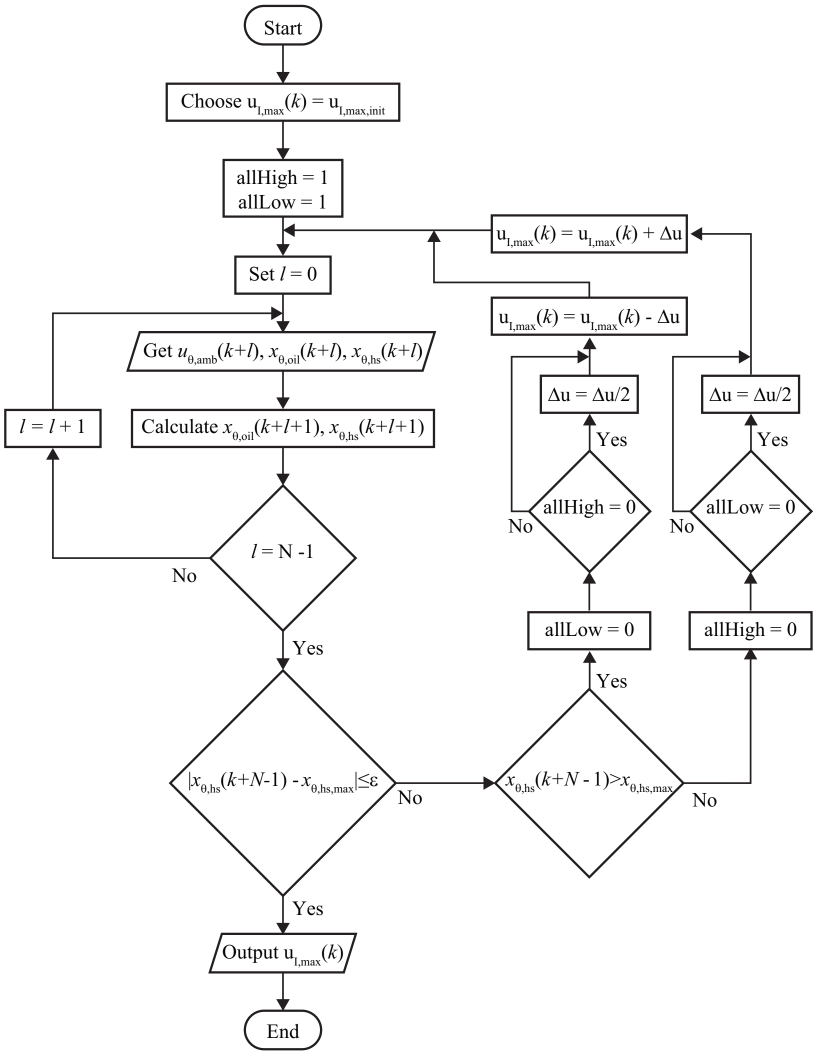

Figure B.1: Algorithm based on the bisection method. ε is the tolerance of the calculation. Δu is the adjustment to the loading.

Appendix C

IEEE 14 Bus Network Data

IEEE 14 bus network used in this thesis is illustrated by the one line diagram in Figure C.1. This example is taken from [36].

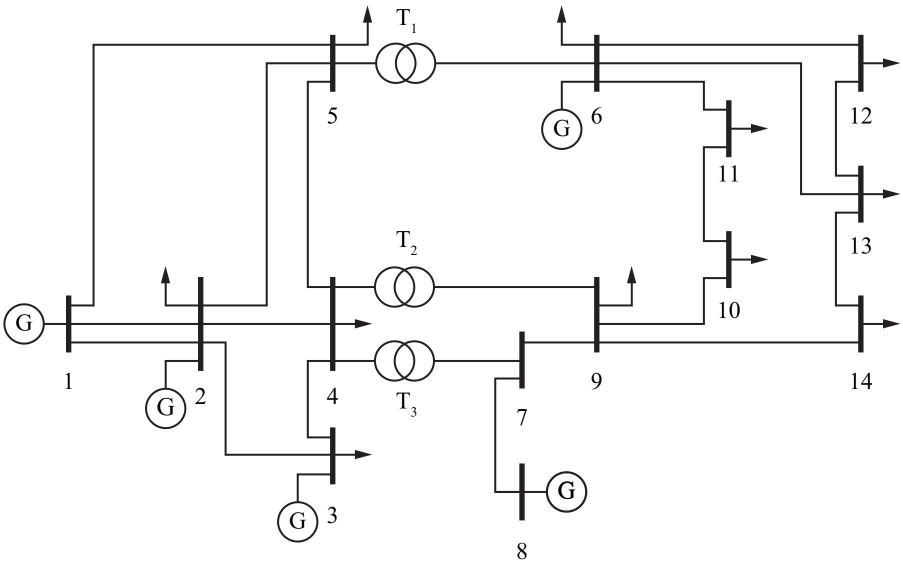

Figure C.1: IEEE 14 bus network [36] used for this thesis.

The bus data of the network is given in Table C.1.

Table C.1: Bus data of IEEE 14 bus network.

N_{bus}	T_{bus}	V_m	Q_{max}	Q_{min}	G_L	B_L
1	3	1.060	–	–	0.0	0.0
2	2	1.045	50.0	-40.0	0.0	0.0
3	2	1.010	40.0	0.0	0.0	0.0
4	0	–	–	–	0.0	0.0
5	0	–	–	–	0.0	0.0
6	2	1.070	24.0	-6.0	0.0	0.0
7	0	–	–	–	0.0	0.0
8	2	1.090	24.0	-6.0	0.0	0.0
9	0	–	–	–	0.0	0.19
10	0	–	–	–	0.0	0.0
11	0	–	–	–	0.0	0.0
12	0	–	–	–	0.0	0.0
13	0	–	–	–	0.0	0.0
14	0	–	–	–	0.0	0.0

where N_{bus} is the bus number, T_{bus} is the type of the bus given by:

- 0 - Unregulated load, PQ-bus: constant active power P and constant reactive power Q,
- 1 - Hold reactive power generation Q within voltage limits, (PQ-bus),
- 2 - Hold voltage within reactive power limits (gen, PV: constant active power P and voltage V),
- 3 - Hold voltage and angle (swing, V-Theta) (must always have one in a network island).

V_m is reference voltage of regulated bus in p.u., Q_{max} is maximum reactive power in MVAR, Q_{min} is minimum reactive power in MVAR, G_L shunt conductance in p.u., and B_L is shunt susceptance in p.u.

The branch data of the network is given in Table C.2.

Table C.2: Branch data of IEEE 14 bus network.

$N_{\text{from bus}}$	$N_{\text{to bus}}$	R_{Line}	X_{Line}	B_{Line}
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.0340
2	5	0.05695	0.17388	0.0346
3	4	0.06701	0.17103	0.0128
4	5	0.01335	0.04211	0.0
4	7	0.0	0.20912	0.0
4	9	0.0	0.55618	0.0
5	6	0.0	0.25202	0.0
6	11	0.09498	0.19890	0.0
6	12	0.12291	0.25581	0.0
6	13	0.06615	0.13027	0.0
7	8	0.0	0.17615	0.0
7	9	0.0	0.11001	0.0
9	10	0.03181	0.08450	0.0
9	14	0.12711	0.27038	0.0
10	11	0.08205	0.19207	0.0
12	13	0.22092	0.19988	0.0
13	14	0.17093	0.34802	0.0

where $N_{\text{from bus}}$ is the from bus number of the branch, $N_{\text{to bus}}$ is the to bus number of the branch, R_{Line} the resistance of the branch in p.u., X_{Line} the reactance of the branch in p.u., B_{Line} , T_{bus} is the line charging of the branch in p.u.

The cost of generation used in this thesis is given by:

$$\text{Generation cost} = \mathrm{C}_2 \times P_{\text{gen}}^2 + \mathrm{C}_1 \times P_{\text{gen}}, \tag{C.1}$$

where P_{gen} is the active power generation. C_1 and C_2 are cost coefficients.

Coefficients C_1 and C_2 are listed in Table C.3.

Table C.3: Coefficients of generation costs.

Generator Bus N_{bus}	C_1	C_2
1	0.0430293	20
2	0.25	20
3	0.01	40
6	0.01	40
8	0.01	40

Appendix D

Thermal parameters of transformers

The IEEE 14 bus network used in Chapter 4 has three transformers of rating 50 MVA, 17 MVA, and 40 MVA. The thermal parameters of these transformer are chosen according to the guideline provided by IEC standard 60076, Power transformers - Part 7: Loading guide for oil-immersed power transformers [26]. The thermal parameters for medium and large transformer provided in the standard are considered. All of the transformers are considered to have ONAN (Oil Natural Air Natural) cooling system. The thermal parameters used are presented in Table D.1

Table D.1: Parameters of transformers used in the thermal model of the case study in Chapter 4.

Parameter	**Value**	**Parameter**	**Value**
$\theta_{\mathrm{oil,rated}}$	82°C	$\tau_{\mathrm{wdg,rated}}$	10 min.
$\theta_{\mathrm{oil,i}}$	38.3°C	$\theta_{\mathrm{hs,i}}$	38.3°C
$\Delta\theta_{\mathrm{hs,rated}}$	26 K	R	6
$\Delta\theta_{\mathrm{oil,rated}}$	52 K	n	0.25

Appendix E

Introduction to UML

Unified Modeling Language (UML) can be used in modeling software projects. UML defines twelve types of diagrams, organized in three categories. The diagrams used in this thesis are described in the following sections.

Parts of this appendix have been published in [20].

E.1 Structural diagrams

Structural diagrams are used to model the static structure of a system. They show the static relationships between classes. Class diagrams are used to describe the structure of classes within a system.

E.1.1 Class diagram

A class is denoted by a box with the class name in bold at the top (Figure E.1). A class could have attributes which describe its properties. The class also contains operations/methods which describe functions/procedures associated with the class. The attributes of the class appear below the class name. The key operations of the class appear below the attributes.

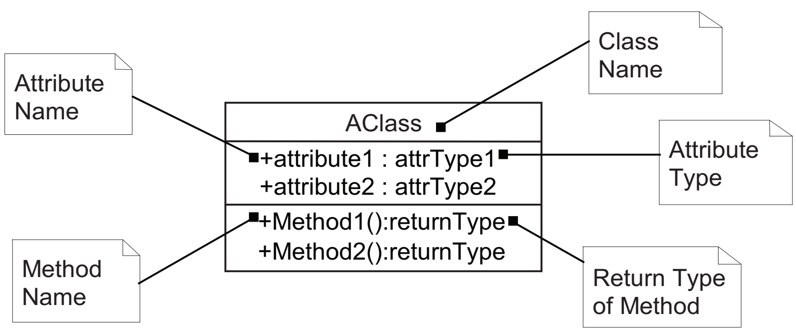

Figure E.1: A class notion.

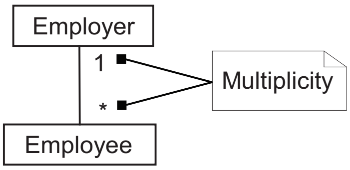

Figure E.2: Example of associations.

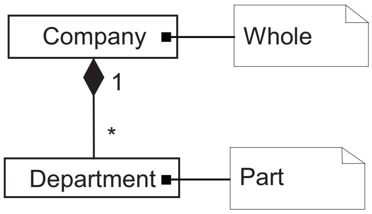

Figure E.3: Example of composition.

E.1.2 Relationship

UML also defines relationship between classes. The relationships used in this thesis are described in the following sections.

Association

Associations represent a relationship between instances of classes. A line connecting both classes represents their association (Figure E.2). The multiplicity of a relationship is represented by numbers, which are printed next to each end of the association. An asterisk (*) indicates a many (zero or more) multiplicity. The example presented in Figure E.2 shows an association between an employer and its employees. In this case, one employer could be associated to multiple employees, which implies one employer could have many employees.

Composition

Composition is a whole/part relationship in which a class (the whole) contains another class (the part) and creation and destruction of the part is the responsibility of the whole. It shows ownerships of classes and is represented by a line with a filled diamond shaped end. As shown in Figure E.3, the diamond shaped end of the relationship is in the owner's (the whole's) side. The example given in Figure E.3 depicts that a company consists of many department.

Inheritance

Inheritance (also known as generalization) is used for modeling a kind-of-relations. It is represented by a line ending with a triangle. As illustrated in an example given in Figure E.4, the triangular end is towards the parent class that is the department class. Administration

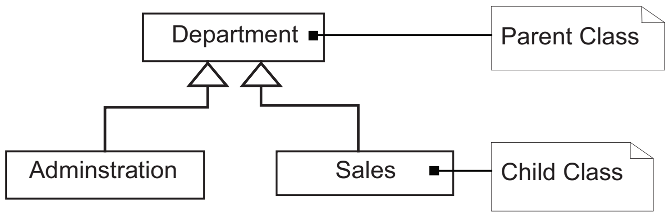

Figure E.4: Example of Inheritance.

class and sales class is a kind of department class. Thus these child classes automatically inherit attributes and methods of their parent class.

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